Collective Perception in Vehicular Ad-hoc Networks

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Kurzfassung

Im Zusammenhang mit den aktuellen Entwicklungen im Themenbereich automatisch fahrender Fahrzeuge spielt die Einführung der Fahrzeug-zu-Fahrzeug-Kommunikation eine zunehmend wichtige Rolle, um langfristig *kooperatives Fahren* zu realisieren. Eine Voraussetzung für dessen Umsetzung ist dabei die umfassende Wahrnehmung der aktuellen Fahrumgebung. Jedes Fahrzeug erstellt dafür ein sogenanntes Umfeldmodell, welches Informationen über andere Verkehrsteilnehmer und Objekte beinhaltet. Eine wichtige Datenquelle für dieses Modell sind zum einen lokale Umfeldsensoren, welche implizites Wissen über die aktuelle Fahrumgebung beisteuern. Zum anderen kann dem Umfeldmodell bei einer direkten Kommunikationsverbindung mit anderen Verkehrsteilnehmern auch explizites Wissen hinzugefügt werden.

Im Rahmen dieser Arbeit wird ein Konzept zur Realisierung der sogenannten *kollektiven Wahrnehmung* entwickelt: Hierbei wird Fahrzeugen der Austausch lokaler Sensordaten mit anderen Verkehrsteilnehmern unter Verwendung der Fahrzeug-zu-Fahrzeug-Kommunikation ermöglicht. Somit können zukünftige Fahrerassistenzfunktionen auf ein umfassenderes Umfeldmodell zugreifen.

Den im Rahmen der Arbeit durchgeführten Analysen liegt ein fahrzeugbasiertes Adhoc Netzwerk zugrunde, welches auf dem europäischen IEEE 802.11p basierten ITS G5 Protokollstapel beruht. Die Effektivität der Technologie fußt hierbei auf der Existenz der sogenannten *kritischen Masse*: Eine ausreichende Anzahl an Kommunikationspartnern muss zugegen sein, damit der Technologie ein Nutzen zugemessen werden kann. Die Verbreitung der Technologie kann jedoch durch indirekte Effekte unterstützt werden.

Die *kollektive Wahrnehmung* ist ein Repräsentant dieser indirekten Effekte, da die Informationsdichte in dem zwischen den Fahrzeugen bestehenden Netzwerk selbst bei niedrigen Marktausstattungsraten erhöht wird. Im Zentrum steht dabei die Einführung eines neuen Nachrichtenformates, welches als Vehikel für den Austausch von Sensordaten im Netzwerk dient. Die Entwicklung dieser Nachricht wird dabei von zwei Perspektiven beeinflusst: Die Sicht der fahrzeugseitigen Assistenzsysteme und deren Datenfusionsalgorithmen beeinflusst die notwendigen Inhalte der Nachricht. Weiterhin werden aus der Netzwerksicht durch Mechanismen wie denen der Lastkontrolle und den bestehenden Nachrichtengrößenbeschränkungen spezifische Anforderungen gestellt.

Das im Rahmen dieser Arbeit erstellte Konzept der *kollektiven Wahrnehmung* beinhaltet dabei beide Perspektiven: Mikroskopische Analysen identifizieren die notwendigen Nachrichteninhalte und spezifizieren Anforderungen an empfangene Daten aus Sicht der Sensordatenfusion. Komplementäre makroskopische Analysen verwenden eine umfangreiche, im Rahmen der Arbeit entwickelte Simulationsumgebung, um das Potential des Konzeptes sowie die aus dem Protokollstapel resultierenden Einschränkungen zu identifizieren.

Beide Untersuchungen werden dabei zur Erstellung eines ganzheitlichen Konzeptes für die *kollektive Wahrnehmung* verbunden.

Abstract

In combination with the current developments in the area of automatically driving vehicles, the introduction of inter-vehicle communication plays a crucial role for realising the long-term objective of what is known as *cooperative driving*. A cornerstone for the expansion of automated vehicles is their thorough understanding of the current driving environment. For this purpose, each vehicle generates an environment model containing information about other perceived traffic participants and objects. Local perception sensors are important data providers for this model, as they contribute implicit knowledge about the environment. In combination with a direct communication link between traffic participants, explicit knowledge can be added to the environment model as well.

The key concept developed within this thesis is called *Collective Perception*: it focuses on sharing data gathered by local perception sensors of one vehicle with other traffic participants by means of inter-vehicle communication. As a result of this concept, future applications relying on a comprehensive understanding of the current driving environment are made feasible.

The analyses presented in this thesis employ a vehicular ad-hoc network (VANET) based on the standardised framework of the European IEEE 802.11p-based ITS G5 protocol stack for inter-vehicle communication. The effectiveness of the technology relies on an existing communication link between a sufficient number of communication partners — the critical mass. The expansion of inter-vehicle communication, however, can be supported by capacitating indirect effects.

Collective Perception is one representative of these effects, as the information density within the network between the vehicles is increased, even at low market penetration rates. At the core of *Collective Perception* stands the introduction of a message format which serves as a vehicle for the exchange of sensor data within a VANET. The development of the message is influenced by two perspectives: First, the vehicle perspective affects the relevant contents of the message required by data-fusion processes and application algorithms. Second, from the network perspective, constraints resulting from the network stack and effects caused by congestion control mechanisms have to be considered.

The development of *Collective Perception* addresses both perspectives: Microscopic analyses provide insights to the required data to be exchanged and the challenges of a fusion process for local and remote sensor data. Complementary macroscopic analyses employ an extensive network simulation framework to determine the effectiveness of *Collective Perception* as well as its limitations due to congestion control mechanisms of the ITS G5 protocol stack.

The combination of these findings are used to develop a holistic concept for exchanging sensor data within a VANET.

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Disclaimer

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Ergebnisse, Meinungen und Schlüsse dieser Dissertation sind nicht notwendigerweise die der Volkswagen Aktiengesellschaft.

List of Publications

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- [105] H.-J. Günther, J. Timpner, M. Wegner, R. Riebl, and L. Wolf. 'Extending a holistic microscopic IVC simulation environment with local perception sensors and LTE capabilities'. In: *Vehicular Communications* (2017)

2016

- [107] H.-J. Günther, B. Mennenga, O. Trauer, R. Riebl, and L. Wolf. 'Realizing collective perception in a vehicle'. In: *2016 IEEE Vehicular Networking Conference (VNC)*. 2016, pp. 1–8
- [104] H.-J. Günther, R. Riebl, L. Wolf, and C. Facchi. 'Collective perception and decentralized congestion control in vehicular ad-hoc networks'. In: *2016 IEEE Vehicular Networking Conference (VNC)*. 2016, pp. 1–8
- [106] H.-J. Günther, S. Kleinau, O. Trauer, and L. Wolf. 'Platooning at traffic lights'. In: *2016 IEEE Intelligent Vehicles Symposium (IV)*. 2016, pp. 1047–1053
- [214] J. Timpner, M. Wegner, H.-J. Günther, and L. Wolf. 'High-resolution Vehicle Telemetry via Heterogeneous IVC'. in: *Proceedings of the First International Workshop on Internet of Vehicles and Vehicles of Internet*. IoV-VoI '16. ACM, 2016, pp. 19–24
- [215] J. Timpner, M. Wegner, H.-J. Günther, and L. Wolf. 'Towards a Multi-Protocol Microscopic IVC Simulation Environment for ADASs'. In: *Fachgespräch Inter-Vehicle Communication Berlin* (2016)

2015

- [108] H.-J. Günther, O. Trauer, and L. Wolf. 'The Potential of Collective Perception in Vehicular Ad-hoc Networks'. In: *14th IEEE International Conference on ITS Telecommunications (ITST)*. 2015
- [183] R. Riebl, H.-J. Günther, C. Facchi, and L. Wolf. 'Artery - Extendig Veins for VANET applications'. In: *Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. 2015
- [94] K. Franke, R. Balaghiasefi, M. Düring, and H.-J. Günther. 'A Cooperative Driver Assistance System: Decentralization Process and Test Framework'. In: *7. Tagung Fahrerassistenzsysteme*. 2015

Contents

Acronyms and Symbols

Acronyms

ACC	Adaptive Cruise Control
ACM	Association for Computing Machinery
ADAS	Advanced Driver Assistance System
AF	Aggregated Fusion
AIFS	Arbitrary Inter Frame Space
AL	Association List
ASN.1	Abstract Syntax Notation One
AT	Approximate Transformation
BER	Basic Encoding Rules
BSA	Basic Set of Applications
BSP	Basic System Profile
BSS	Basic Service Set
BTP	Basic Transport Protocol
C-ACC	Cooperative Adaptive Cruise Control
C2C-CC	Car 2 Car Communication Consortium
CAM	Cooperative Awareness Message
CAN	Controller Area Network
CBR	Channel Busy Ratio
CCH	Control Channel
CDAS	Cooperative Driver Assistance System
CDD	Common Data Dictionary
CDF	Cumulative Distribution Function
CEN	European Committee for Standardization
CPM	Cooperative Perception Message
CSM	Cooperative Sensing Message
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
D2D	Device-to-Device
DCC	Decentralised Congestion Control
DDS	Data Distribution Service
DENM	Decentralized Environmental Notification Message

DP	DCC Profile
DSRC	Dedicated Short Range Communication
ECU	Electronic Control Unit
EDCA	Enhanced Distributed Coordination Access
ENU	East, North, Up
EPM	Environmental Perception Message
ESC	Electronic Stability Control
ESR	Electronic Scanning Radar
ETC	Electronic Toll Collection
ETSI	European Telecommunication Standards Institute
FCD	Floating Car Data
FoV	Field-of-View
FSM	Finite State Machine
GEM	Global Environment Model
GEMO	Global Environment Model Object
GN	Geo Networking
GNSS	Global Navigation Satellite System
HiL	Hardware in the Loop
HMI	Human Machine Interface
ICRW	Intersection Collision Risk Warning
IDE	Integrated Development Environment
IEEE	Institution of Electrical and Electronics Engineers
IMU	Inertial Measurement Unit
ISO	International Organization for Standardization
ITS	Intelligent Transportation System
ITS-S	ITS-Station
IVC	Inter-Vehicle Communication
LCRW	Longitudinal Collision Risk Warning
LDM	Local Dynamic Map
LEM	Local Environment Model
LEMO	Local Environment Model Object
LF	Local Fusion
Lidar	Light detection and ranging
LLC	Logical Link Control
LoS	Line-of-Sight

LRR	Long Range Radar
LTE	Long Term Evolution
LTP	Local Tangential Plane
MAC	Medium Access Control
MANET	Mobile Ad-hoc Network
MCO	Multi Channel Operation
MIB	Management Information Base
MSDU	MAC Service Data Unit
NHTSA	National Highway Traffic Safety Administration
OEM	Original Equipment Manufacturer
OFDM	Orthogonal Frequency Division Multiplexing
OMNeT++	Objective Modular Network Testbed in C++
OSI	Open Systems Interconnection
PCA	Principal Component Analysis
PKI	Public Key Infrastructure
PROMETHEUS	Program for European Traffic with Efficiency and Unprecedented Safety
QoS	Quality of Service
Radar	Radio detection and ranging
RCM	Request for Cooperation Message
RHS	Road Hazard Signalling
RMS	Root Mean Square
RSU	Roadside Unit
SAE	Society of Automotive Engineers
SCH	Service Channel
SDS	Self Driving System
SHB	Single Hop Broadcasting
SiL	Software in the Loop
simTD	Safe Intelligent Mobility - Test Field Germany
SLAM	Simultaneous Localisation and Mapping
SLR	Systematic Literature Review
SNAP	Subnetwork Access Protocol
SPaT	Signal Phase and Timing
SUMO	Simulation of Urban Mobility

TC	Technical Committee
TCP	Transfer Control Protocol
TraCI	Traffic Command Interface
TTC	Time To Collision
UAV	Unmanned Aerial Vehicle
UDP	User Datagram Protocol
UPER	Unaligned Packed Encoding Rules
US-DOT	United States Department of Transportation
UTM	Universal Transverse Mercator
V2X	Vehicle-to-X
VANET	Vehicular Ad-hoc Network
VDP	Vehicle Data Provider
Veins	Vehicles in network simulation
VICS	Vehicle Information and Communication System
VTD	Virtual Test Drive
WAVE	Wireless Access in Vehicular Environments
WGS84	World Geodetic System of 1984
WSM	WAVE Short Message
WSN	Wireless Sensor Network

Symbols

Matrices are denoted in upper case bold letters ($\boldsymbol{A}$), vectors are represented as lower case bold letters ($\boldsymbol{a}$) and corresponding elements are denoted in lower case italic using the same letter (a). Transpose operations are denoted by a superscripted ^{T}.

Symbol	**Unit**	**Description**
$\bar{\rho}$	-	Arithmetic mean of random variable ρ
$\alpha_\zeta^{\mathrm{maj}}$	m	Orientation of major radius of position error ellipse for vehicle ζ
k_s	-	Awareness ratio for sensor s
k_s^w	-	Weighted awareness ratio for sensor s
$\mathbf{C}$	specific	Covariance matrix
CBR_m	-	Channel Busy Ratio based on measurement m
CBR_t	-	Smoothed Channel Busy Ratio for time-window t
$\mathrm{Cov}(\rho,\tau)$	specific	Multivariate covariance of random variables ρ and τ
σ_ρ^2	specific	Variance of random variable ρ
$E(\rho)$	specific	Expected value of random variable ρ
$\mathbf{J}$	specific	Jacobian matrix
κ	rad	Roll angle of a vehicle in ISO 8855 reference frame
$\boldsymbol{\lambda}_{\mathrm{WGS}}$	° (degree)	Longitude in WGS84 reference frame
λ_ζ	° (degree)	Current longitude of ITS-S ζ in WGS84 reference frame
$\mathcal{N}(\boldsymbol{\mu}_\zeta,\boldsymbol{C}_\zeta)$	specific	Multivariate normal distribution with location $\boldsymbol{\mu}_\zeta$ and covariance $\boldsymbol{C}_\zeta$
$\boldsymbol{\varphi}_{\mathrm{WGS}}$	° (degree)	Latitude in WGS84 reference frame
φ_ζ	° (degree)	Current latitude of ITS-S ζ in WGS84 reference frame
ψ	rad	Yaw angle of a vehicle in ISO 8855 reference frame
r_ζ^{maj}	m	Major radius of position error ellipse for vehicle ζ
r_ζ^{min}	m	Minor radius of position error ellipse for vehicle ζ
θ_ζ	° (degree)	Heading in LTP reference frame for vehicle ζ
σ_ζ	° (degree)	Heading in WGS84 reference frame for vehicle ζ
σ	specific	Standard deviation of random variable
β	rad	Pitch angle of a vehicle in ISO 8855 reference frame
TTC	s	Time to Collision
v	m/s	Velocity
$\boldsymbol{x}_\zeta$	m	X-axis in ISO 8855 reference frame
$\boldsymbol{x}_{\mathrm{LTP}}$	m	X-axis in LTP reference frame
$\boldsymbol{y}_\zeta$	m	Y-axis in ISO 8855 reference frame
$\boldsymbol{y}_{\mathrm{LTP}}$	m	Y-axis in LTP reference frame
$\boldsymbol{z}_{\mathrm{WGS}}$	m	Altitude in WGS84 reference frame
$\boldsymbol{z}_\zeta$	m	Z-axis in ISO 8855 reference frame
$\boldsymbol{z}_{\mathrm{LTP}}$	m	Z-axis in LTP reference frame
ζ	-	Arbitrary vehicle or object identifier

1 Introduction

Today's vehicles can be equipped with a multitude of Advanced Driver Assistance Systems (ADASs), increasing both safety and comfort for the driver and for other traffic participants. Systems such as the Adaptive Cruise Control (ACC), parking or a lane-keeping assistant support the driver in his task of controlling the vehicle, especially in monotonous driving situations.

Common to all ADASs is their working principle based on the perception and sensing of the environment: in analogy to the driver using his organs of perception for sensing the environment, a vehicle requires dedicated sensors to first create an environment model of its current surroundings. In the second step, the driver's brain has to interpret the perceived environment, as does the vehicle by using its computing resources for interpreting the current driving scene.

Bringing all of these systems together, the long-term goal of the automotive industry to introduce fully automated vehicles, or so-called Self Driving Systems (SDSs), is taking the next decisive step. Table 1.1 depicts the *levels of automation* for on-road motor vehicles, as defined by the Society of Automotive Engineers (SAE) [211]. The society introduces two main categories of SDSs, that depend on the mode of perception of the vehicle's environment. ADASs such as the ACC mentioned above conform to the SAE-levels 1 or 2, in which the driver is considered as the key component. At these levels, the driver is still responsible for monitoring the driving environment as well as for performing the dynamic driving task. However, in the context of SDSs of level 3 and above, the driver is no longer responsible for the perception of the vehicle's environment. Instead, the automated system has to be equipped with technologies for continuously monitoring the current driving environment.

Next to on-board sensor technologies, the introduction of a direct communication link between vehicles has a great potential for the expansion of SDSs. Not only can communication-enabled vehicles share information about their current position and driving state, but also about their current driving environment. Furthermore, current research aims at developing so-called *cooperative driving* applications, where automated vehicles exchange information related to their driving behaviour for the purpose of cooperating with each other [94]. Exchanging this information relies on an existing radio communication link between these traffic participants, which is commonly known as Vehicle-to-X (V2X) communication, where the variable *X* can be replaced by an arbitrary communication partner [26, 175]. In Europe, the so-called ETSI ITS G5 standards specify the communication technology for direct inter-vehicle communication based on a Vehicular Ad-hoc Network (VANET).

Table 1.1.: Levels of automation according to SAE J3061 [211]

Environment Monitoring	**SAE Level**	**Name**	**Description**
Human driver	0	No Automation	Full-time performance by human driver of all aspects of the dynamic driving task.
	1	Driver Assistance	Driving-mode specific execution by a driver assistance system with the expectation that the human driver performs all remaining aspects of the dynamic driving task.
	2	Partial Automation	Driving-mode specific execution by one or more driver assistance systems for steering and acceleration based on the perception of the environment with the expectation that human driver performs the remaining parts of the dynamic driving task.
Automated driving system	3	Conditional Automation	Driving-mode specific execution by a driver assistance system with expectation that human driver will respond appropriately to a request to intervene.
	4	High Automation	Driving-mode specific execution by a driver assistance system even if the driver does not respond appropriately to a request to intervene.
	5	Full Automation	Full-time performance by an automated system of all aspects of the dynamic driving task.

Next to the realisation of Self Driving Systems, advances in the development of ADASs also play a crucial role in reducing the number of accidents. Several factors contributed to a decrease in road accidents, especially since 1970 when accident rates reached their peak: the high number of 21.332 fatalities due to road accidents in Germany alone has been reduced by 83.3 % in 2015, albeit the number of registered vehicles has increased by more than 62 % [23]. Next to legislative regulations, improved road constructions and rescue services, as well as advancements in the development of vehicle safety systems vastly contributed to the reduction of casualties caused by traffic accidents. The meta-study of Vaa et al. presents an analysis of the effectiveness of different assistance systems with respect to road accidents. The authors found that even though the working-principles of some systems such as anti-lock brakes are compensated due to behavioural adaptations, i.e. increased driving speeds, most of the systems, such as the Electronic Stability Control (ESC), have a positive impact towards reducing road accidents. Despite behavioural adaptations, future ADASs exhibit an even larger potential to further reduce road casualties [221]. Furthermore, misbehaviour of the driver accounts for 88 % of the accidents in Germany: false turning behaviour, ignored right-of-way, exiguous distance to other traffic participants and exalt speeds are only some of them [23].

A dedicated communication link between vehicles, in combination with the prospective ADAS applications relying on this communication link, exhibit a large potential to further increase road safety. A study of the US National Highway Traffic Safety Administration

(NHTSA) estimates that up to 79 % of the registered accidents would be addressed by V2X applications. In combination with automated vehicles, the NHTSA states that 97 % of the light-vehicle crashes and up to 86 % of heavy-truck crashes will be addressed by the introduction of vehicular communication [161]. Although not every crash might be avoided by V2X communication in combination with SDSs altogether, the accident severity might be reduced substantially. As one of the countries with the lowest accident rates in the world, Sweden enforced the so-called *Vision Zero*, prioritising the eradication of road fatalities [217]. Germany's *Traffic-Safety Program of 2011* also assigns ADASs and V2X communication a crucial role for reaching a reduction of fatalities by 40 % by the year of 2020 [125].

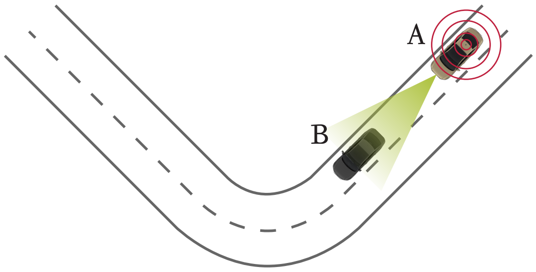
Consequently, combining SDSs and V2X communication contributes to increasing road safety in the years to come. This thesis aims at providing a technology which can be employed by future ADAS applications to further reduce accident figures. The developed concept shares the data provided by the increased number of local perception sensors on the market to create a mutual, more comprehensive awareness for the vehicle's current driving environment.

1.1. Introducing Collective Perception

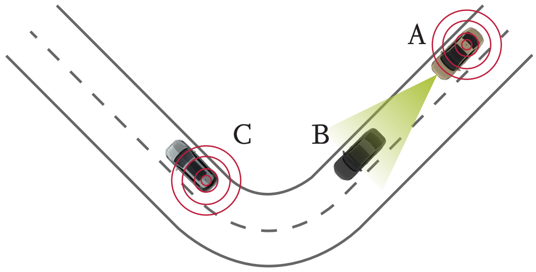
The nature of ADASs is always a reaction based on the available information: a vehicle with activated ACC decelerates as a reaction to a decelerating vehicle detected in front. Another example could be a steering intervention, when a driver tries to change the lane although another vehicle approaches on the neighbouring lane. The information of all sensors of a vehicle are private to the collector and lead to the aforementioned reactive behaviour of ADASs. Furthermore, today's algorithms of ADASs of one vehicle cannot take it for granted to be perceived by another vehicle - the result of which is a limited field of application for ADASs.

However, this changes when traffic participants actively exchange information, e.g. by means of V2X communication. The installation rate of ADASs increased continuously over the last years and will gain even more momentum over the years to come [37]. With an increasing number of vehicles equipped with ADASs, the available number of perception sensors increases as well. Therefore, this thesis introduces the concept of *Collective Perception*, by at the same time combining V2X communication and the augmented availability of local perception sensors in order to mutually extend the perception range of all communicating vehicles.

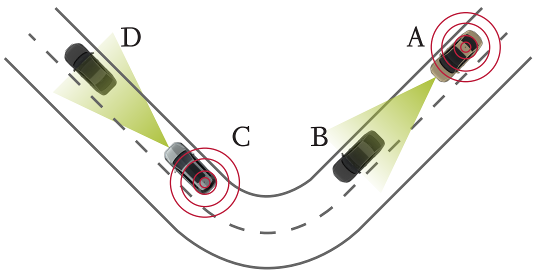
Figure 1.1 shows the idea of the concept in more detail. In Figure 1.1a, vehicle A is aware of vehicle B as it uses its local sensors to perceive the current driving environment. With the help of these sensors, information such as the relative distance to detected objects can be retrieved and conventional ADASs, such as an ACC application, can employ this information in their algorithms. With the addition of V2X communication, vehicle A is made aware of vehicles located outside of the Field-of-View (FoV) of its local perception sensor, as displayed in Figure 1.1b. Since V2X communication enables objects to publish data about themselves in the network, the quantity of information about an object is more



(a) Local perception



(b) Local perception and V2X



(c) Collective Perception

Figure 1.1.: The concept of *Collective Perception* by means of exchanging sensor information

extensive compared to the data gathered from conventional local perception sensors. The quality of this information, however, is not necessarily superior to data gathered from local perception sensors [96]. Figure 1.1c displays the concept of *Collective Perception* by exchanging sensor information between V2X enabled vehicles as well. In addition to those vehicles perceived by its local sensors and by V2X communication, it is made aware of the presence of vehicle D by vehicle C. Although vehicle A is not able to perceive vehicle D by its on-board sensors and although vehicle D is not equipped with V2X communication technologies, its presence is published in the inter-vehicle network. Sharing perceived objects between traffic participants allows for an extension of the FoV of V2X enabled vehicles beyond their current Line-of-Sight (LoS). As a result, *Collective Perception* increases a vehicle's awareness for the objects present in its vicinity.

Along with the benefits of introducing a direct communication link between traffic participants comes the challenge of any technology relying on the presence of others: the so-called network effect. Liebowitz et al. differentiate two elements of any good or technology whose value depends on its expansion [144]. The autarky-value of the technology is the immediate value resulting from its sole presence. The more important part of the value is added by the synchronisation-element, which results from the interaction with others [144]. Generally, a critical mass needs to exist, representing the minimum number of required communication partners for the user to have an advantage or value of buying and using the technology.

When applying the concept of network effects to V2X technology and the automotive industry, it becomes apparent that both customers and Original Equipment Manufacturers

(OEMs) require incentives to buy and develop the technology. Customers will only spend money on a system relying upon V2X communication, if its advantage is evident and if they can experience it frequently. Unless requested by legal requirements, OEMs will only spend money on developing V2X technologies if there are enough customers willing to pay for it [151]. Therefore, any means of reducing the critical mass required for a technology to be adopted should be pursued [50, 144]. As demonstrated within this thesis, the principle of *Collective Perception* can serve as an enabler towards the reduction of the required critical mass, as the technology increases the number of published objects within the inter-vehicle network.

1.2. Contributions

The research presented in this thesis provides the following contributions for shared sensor data in a VANET:

- **Introduction of data containers for *Collective Perception*:** The first contribution introduces data containers for *Collective Perception* complying with existing ETSI ITS G5 standards. These containers provide both a generic description of perceived objects and a description of the sensory capabilities of the disseminating vehicle. Incorporating these containers, two different message formats are proposed: the Environmental Perception Message (EPM) as a stand-alone message, as well as the extended Cooperative Awareness Message (CAM) as an upgrade to an already standardised message format. The data containers and message formats are introduced in chapter 5.

- **Introduction of local perception sensors in network simulations:** The second contribution provides dedicated application modelling and local perception sensors to the popular Vehicles in network simulation (Veins) framework [105, 203]. Simulated vehicles can be equipped with multiple local perception sensors. Data gathered by these sensors is then maintained within an individual environment model. The extension provides the necessary tools to study the effects of *Collective Perception* in a large scale VANET and is made publicly available. A description of the extension is provided in section 6.3.

- **Demonstration of the potential of shared sensor data:** The third contribution demonstrates the potential of *Collective Perception*. Employing the simulation framework extended by the second contribution, a significant increase in a vehicle's awareness can be observed, when sharing sensor data within a VANET by utilising the message formats of the first contribution. Especially at low market penetration rates for V2X communication, *Collective Perception* increases the number of objects known to a particular vehicle. Section 6.5 provides the findings of the simulation study in more detail.

- **Identification of shortcomings of the European V2X communication stack for realising *Collective Perception*:** The fourth contribution analyses the feasibility of *Collective Perception* within the context of the European V2X communication stack. An extensive simulation study compares both proposed message formats in combination with different stack parametrisations to show that for increased communication channel loads, messages are being dropped prior to being enqueued into the transmission queues of the network device. The simulations show that the congestion control mechanism of the communication stack drops these messages, although the communication channel exhibits sufficient capacity to accommodate these messages. Section 6.6 details the analysis of the European V2X communication stack in the context of *Collective Perception*.
- **Development of a high level environment model architecture:** The fifth contribution introduces a high-level environment model architecture for incorporating V2X messages in the representation of a vehicle's current driving environment. The architecture provides two separate object lists to account for forged or falsified received V2X data which might alter the representation of the environment: the first list provides objects verified by on-board sensors only, the second list provides a more comprehensive description by including objects received by V2X messages. The architecture is detailed in section 7.1.
- **Presentation of an error propagation model:** The sixth contribution is an error propagation model for estimating the achievable accuracy for object descriptions, when incorporating objects received from others in an environment model. The accuracy of position and state estimates of objects received by V2X messages not only depends on the measurement accuracy of the local perception sensors, but also on the accuracy of the employed localisation solution. The model provides a mechanism for calculating the propagated error, when considering received objects in the environment model. Section 7.2 provides the sensitivity analysis of the error propagation model.
- **Validation of the concept of *Collective Perception*:** The seventh contribution is an implementation of the developed concept in automated vehicles. The effectiveness of *Collective Perception* is validated in a collision avoidance scenario with two automated vehicles on a race-track: by sharing sensor data between these vehicles, a significant increase in the vehicles' awareness can be observed. For this scenario, *Collective Perception* almost triples the time available for planning a safe obstacle avoidance trajectory compared to the same scenario without communicating vehicles. A detailed validation is shown in section 7.3.

1.3. Outline

This thesis is separated into three logical parts, as detailed in Figure 1.2.

The first part introduces the subject of *Collective Perception* and describes the relevance of V2X communication for future automated cooperative driving applications. Chapter 2 describes the role of *Collective Perception* in the context of cooperative driving and provides related information towards the working-principles of V2X communication. As the data shared in the context of *Collective Perception* is based on measurements of local perception sensors, the chapter also introduces the working principles of those sensor types used within this thesis. Chapter 3 deduces network- and vehicle-specific research questions which are answered in subsequent chapters of the thesis.

The second part focuses on the development of a holistic concept for *Collective Perception*. Chapter 4 provides the results of a thorough systematic literature review in the area of shared sensor data, including related disciplines. The chapter includes a summary of relevant research projects in the automotive field, which also focus on sensor-data exchange. Building upon the presented state-of-the-art, chapter 5 presents the requirements, the developed message formats and mechanisms for realising *Collective Perception*.

The two chapters of the third part of the thesis present the feasibility of these concepts and may be read independently. Each chapter first introduces the concepts and frameworks to specifically answer the research questions formulated in chapter 3. The macroscopic analyses presented in chapter 6 first introduce a simulation framework which is capable of simulating multiple complete protocol stacks for a large number of vehicles. In a

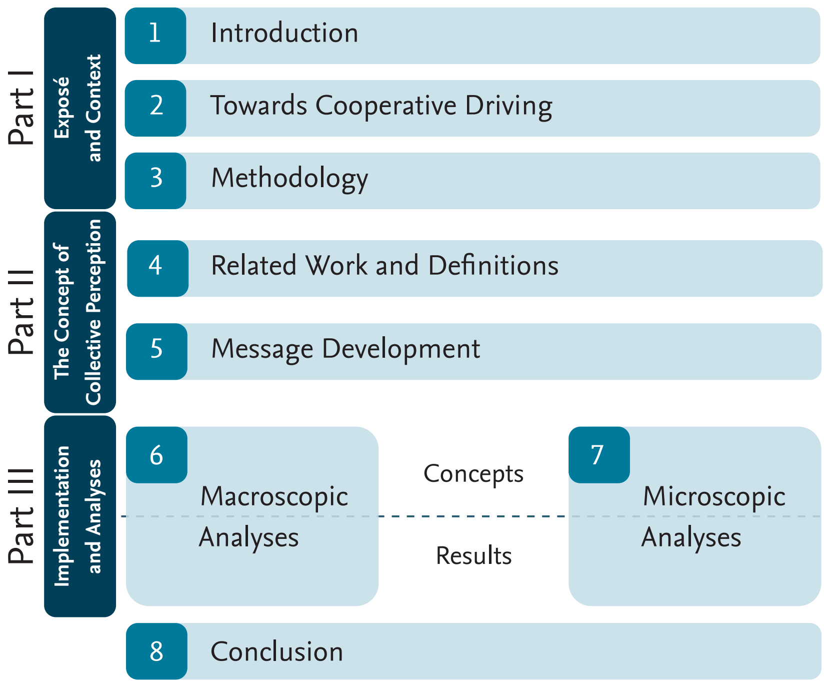


Figure 1.2.: Thesis Outline

second step, this framework is used for answering the research questions related to the inter-vehicle network. The findings not only demonstrate the effectiveness of *Collective Perception* but also indicate the prospective network-related constraints which may hinder the realisation of the concept. The microscopic analyses presented in chapter 7 in turn demonstrate the feasibility of the developed message formats and concepts as part of an implementation of *Collective Perception* in a vehicle. The chapter also develops a model which estimates the propagated measurement error, when considering shared sensor data in ADAS applications. Furthermore, a data-fusion architecture is presented along with a validation of *Collective Perception* in the context of a collision avoidance application for automated vehicles.

Chapter 8 summarises and discusses the findings of the thesis and provides an outlook on further research questions.

2 Towards Cooperative Driving

One of the advantages of V2X communication is the paradigm shift in the field of assistance systems from being reactive to being proactive. V2X communication provides information which cannot be retrieved by using conventional local perception sensors. As a result, novel ADAS applications can become anticipatory and to some extent even exhibit cooperative behaviour. Section 2.1 introduces the technological background of V2X communication technologies. Next to providing the relevant standards and working principles, V2X communication is distinguished from other Inter-Vehicle Communication (IVC) methodologies.

In section 2.2, the working principles of those local perception sensors employed within this thesis are introduced along with the standardised message formats contributing to the vehicle's perception of its driving environment.

In combination with SDSs, V2X communication will improve road safety and increase the passengers' comfort by cooperating with other traffic participants. Section 2.3 therefore puts the concept of *Collective Perception* into the perspective of an architecture for *Cooperative Driving*.

2.1. Inter-Vehicle Communication

Communicating vehicles are one of the cornerstones to promote SDSs as well as to increase road safety, as outlined in chapter 1. The following sections introduce the concept of Intelligent Transportation Systems (ITSs) and provide an overview of the development of vehicular communications. The technologies enabling inter-vehicle communication based on ad-hoc networks and the corresponding standards are provided as well.

2.1.1. Intelligent Transportation Systems

Intelligent Transportation Systems are researched by different disciplines with the common objective of increasing traffic safety and efficiency as well as to protect and to conserve the environment [92]. However, a common definition of the term does not exist. Research in the area of ITSs has been pursued since the late 1980s, resulting from large-scale projects such as the Program for European Traffic with Efficiency and Unprecedented Safety (PROMETHEUS) or the US Automated Highway System project [7, 120]. Since then, ITSs have become an establishment — resulting in the formation of several working-groups (e.g. United States Department of Transportation (US-DOT) ITS Joint Program Office [44]), standardisation-organisations (e.g. European Telecommunication Standards Institute (ETSI) ITS group [62], Institution of Electrical and Electronics Engineers (IEEE) ITS Society [97]) and joint consortia (e.g. Car 2 Car Communication Consortium (C2C-CC) [26]).

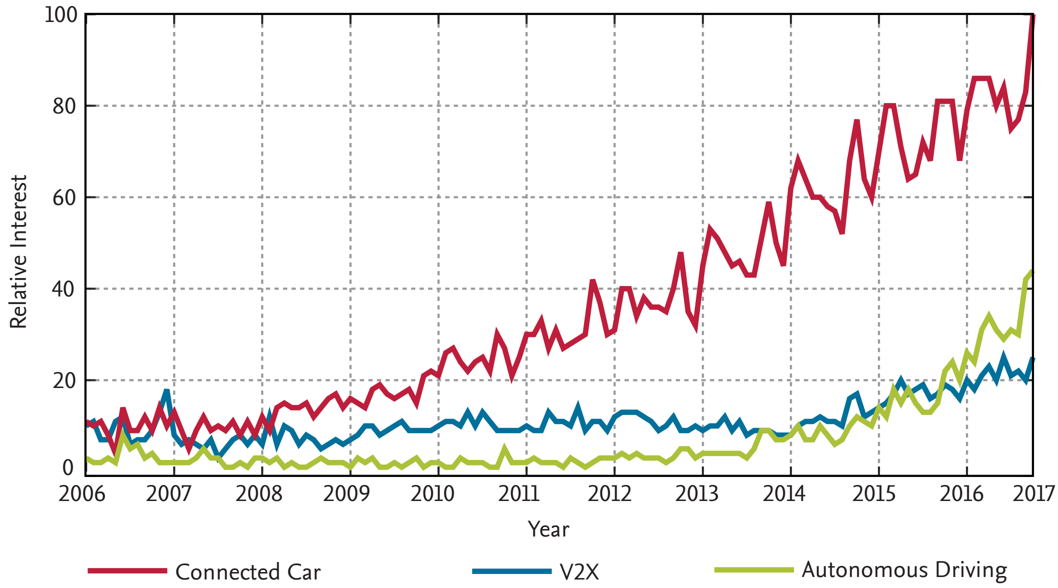


Figure 2.1.: Google Trend data for ITSs [Generated on 10/09/2016]

Within the automotive context, numerous topics are covered in the area of ITSs. Along with the expansion of mobile internet connectivity over the last decade, emerging new players within the automotive industry and the so-called *digitalisation of the car*, public interest in ITSs increased significantly [17, 100, 101]. *Google Trend*[1], a service which has proven to reliably measure present public interest [36], also indicates that ITSs are becoming even more relevant. Figure 2.1 presents the relative interest for three keywords closely connected to this thesis in the area of ITSs:

Connected Car This keyword describes all topics related to vehicle connectivity, such as mobile internet services, vehicle communication and other connected services. The observed increasing public interest can be explained by interpreting the *Connected Car* as a term summarising specific technologies such as SDSs or V2X communication as well as traffic information services.

V2X Public interest in V2X communication only increased by about 5 % over the last two years, whilst it may have been interpreted as a synonym for *Connected Cars* a decade ago. Within this thesis, V2X communication refers to standards and specific technologies for realising a direct data exchange between two or more traffic participants based on an ad-hoc network.

Autonomous Driving This keyword represents the public, though colloquial understanding of SDSs as described in chapter 1. Over the last three years, public interest

1 `https://www.google.com/trends/`, generated on 09/10/2016

increased significantly - along with the number of research projects and companies demonstrating activity in this area.

This thesis focuses on the subject of connected cars, particularly on inter-vehicle communication. In the context of autonomous driving, inter-vehicle connectivity will play an essential role towards coordinating driving manoeuvres and towards improving a vehicle's individual perception capabilities. The following subsections detail the employed communication technologies and working principles.

2.1.2. Connected Vehicles

Throughout the years, research concentrated on different topics in the context of ITSs, such as on vehicles, roads, traffic efficiency and the drivers themselves. Today's efforts focus on methodologies for automating the driving task [175]. Vehicle connectivity thereby plays a crucial role in promoting automated vehicles. Lu et al. differentiate two types of vehicle connectivity [147]: *Intra-Vehicle connectivity* states the need for increased amount of data that needs to be exchanged between Electronic Control Units (ECUs) within the vehicle itself. Over the last years, the number of actuators, sensors and other equipment available in cars increased significantly [20, 111] — and with that the amount of data available within the car itself. Whereas this data renders today's ADAS applications possible, a multitude of novel bus-systems (e.g. Controller Area Network (CAN), FlexRay or Automotive Ethernet) is required to cope with the large amount of data to be distributed [109]. However, wireless communication technologies within a vehicle are mainly suitable for multimedia-applications (e.g. music-streaming) due to comparatively low transmission reliability, data security issues and challenging vehicle geometries [147]. For *Inter-Vehicle Communication (IVC)*, however, wireless communication technologies play a crucial role, as wired connections are not feasible. In this context, different purposes for employing communication have to be differentiated.

Within this thesis, IVC is differentiated into two regimes: *indirect* IVC concerns additional services offered to the driver to provide an ubiquitous internet connection and to enhance driving comfort. Nevertheless, *indirect* IVC relies on the existence of a third party which enables the connectivity between vehicles. Different cellular communication technologies may be employed for *indirect* IVC, such as 3G or Long Term Evolution (LTE). Most available systems periodically send information to an OEM-specific back-end, which, in turn, distributes aggregated information back to the vehicles, e.g. to enhance route guidance or to avoid traffic jams [156]. To name only a few available solutions, BMW's *Connected Drive*, Volkswagen's *Car-Net* or GM's *OnStar* systems rely on integrated cellular connections to provide on-line traffic updates, mobile-office-services and internet access as part of the vehicle's infotainment system [32, 128]. Academic research in the area of *indirect* IVC mainly focuses on privacy aspects and improvements in cellular connection quality [133].

Direct IVC, in turn, focuses on mechanisms for sharing data with other vehicles or traffic participants within a vehicle's vicinity. Data exchange between the communication partners occurs in so-called Mobile Ad-hoc Networks (MANETs), for which a third party or any kind of communication infrastructure is not required. Within the context of vehicular networking, a MANET is also referred to as a VANET, if all communication partners are ITS-Stations (ITS-Ss). In this thesis, VANET-based communication is also referred to as V2X communication, although — in a broader sense — information exchange between two or more vehicles may also be realised by means of *indirect* IVC.

The topic of VANET research has been and still is subject of numerous research projects. Whereas the aforementioned PROMETHEUS project performed some analyses in the area of vehicular communication, recent technological advancements and increased availability of communication components allows for more in-depth research today [237]. One of the most noticeable projects was the German project *Safe Intelligent Mobility - Test Field Germany (simTD)* launched in 2008. The project members, which included all German vehicle manufacturers and some of the largest suppliers, developed a common near-series architecture and performed large-scale field-operational tests with more than 100 vehicles [12].

As a result of the numerous activities in the field of *direct* IVC, several European OEMs and automotive suppliers initiated the *Car 2 Car Communication Consortium* — a non-profit organisation with the objective of creating a European industry standard for V2X communication [26]. The consortium also participated in the formation of the aforementioned ETSI Technical Committee (TC) ITS which is responsible for developing and issuing telecommunication standards in Europe. Three main areas of responsibility and exemplary applications for V2X communication have been identified by the C2C-CC: road safety, traffic efficiency and infotainment [26]. Furthermore, the consortium's memorandum of understanding, signed by all members, postulates a deployment strategy for cooperative ITSs [27].

Due to legal and historical differences in other markets, different limitations regarding the applied communication solution for *direct* IVC exist. A major challenge in the area of V2X communication is the existence of multiple protocol stacks due to differing standards in diverse markets. In Japan, a multitude of technologies will be employed due to already existing communication solutions, such as the Vehicle Information and Communication System (VICS) and the Electronic Toll Collection (ETC) based on infrared, 2.4 GHz and 5.8 GHz Dedicated Short Range Communication (DSRC) [98]. The US, on the other hand, promote the use of the DSRC Wireless Access in Vehicular Environments (WAVE) protocol stack based on the IEEE 802.11p standard [159]. The European standards introduce the so-called ETSI ITS G5 protocol stack, which is also based on the IEEE 802.11p standard and, like its US counterpart, operates within a 5.9 GHz frequency range [123]. All analyses presented in this thesis are based on the European ITS G5 communication stack. Hence, a more detailed presentation is given in subsection 2.1.3.

Truly connected vehicles will combine both *direct* and *indirect* IVC and therefore have to make use of multiple communication technologies. Closely related are the developments in the area of cellular 5G communication, combining multiple communication technologies to provide ubiquitous connectivity, thereby meeting the specific demands of different applications. The benefits of IEEE 802.11p-based local ad-hoc communication may also be realised by means of Device-to-Device (D2D) communication within the licensed frequency bands — offering higher speeds, lower latencies and increased reliability [213, 232]. Next to local ad-hoc communication, however, vehicles are also required to contact and to contribute data to cloud-based services offered by either OEMs or third parties. The *5G Infrastructure Public Private Partnership*, a collaboration of various interest groups within the communication industry and the European Commission, also published a white-paper on the use of 5G technologies within the automotive context. The document compares ITS G5-based communication with available different technologies, such as LTE Release 12 which also includes provisions for direct communication. However, ITS G5 is regarded as a supplementary technology which is required for certain applications and is therefore considered to be part of the 5G architecture [1]. Alieiev et al. outline some of these applications, such as automated overtaking or driving in a platoon, which impose high requirements in terms of latency and reliability [6]. Furthermore, the authors indicate that neither today's LTE-based communication nor ITS G5 satisfy the requirements of these applications under all conditions. Yet another requirement for 5G communication stems from the need of redundant communication mechanisms, especially in the context of automated driving. Hence, 5G communication provides a secondary mechanism for exchanging V2X messages [93]. To coordinate the developments in the area of future cellular applications within the automotive industry, the *5G Automotive Association* has been initialised [192].

2.1.3. ETSI ITS G5

The European Commission's mandate M/453 rendered the ETSI and European Committee for Standardization (CEN) responsible for developing and publishing the standards in the field of ITSs [90]. Whereas the former organisation issues standards for IVC as well as for the communication protocol stack, the latter focuses on the standardisation of applications for traffic efficiency based on infrastructure components [199]. The Commission's mandate followed its decision of 2008, which allocates frequencies in the range of 5.9 GHz and specifies their use within the context of ITSs [89]. Figure 2.2 depicts the assigned frequencies and the dedicated channels for ITS communications. The frequency range between 5.855 GHz and 5.925 GHz has been allocated to be used in conjunction with the ITS G5 communication stack. This spectrum is divided into seven channels, each with a bandwidth of 10 MHz. Furthermore, the Commission assigned specific rules for using these channels. The three channels between 5.875 GHz and 5.905 GHz, referred to as the ITS G5A band, are allocated for safety related applications only, i.e. those applications which aim at reducing the number of fatalities [89]. The so-called Control Channel (CCH) has a centre-frequency of 5.9 GHz and is the primary channel to be used for these applications. The other two channels within this band are so-called Service Channels (SCHs) with secondary and not yet defined use-cases. The ITS G5B band contains two channels between 5.855 GHz and 5.875 GHz which may be employed for non-safety related applications targeting traffic

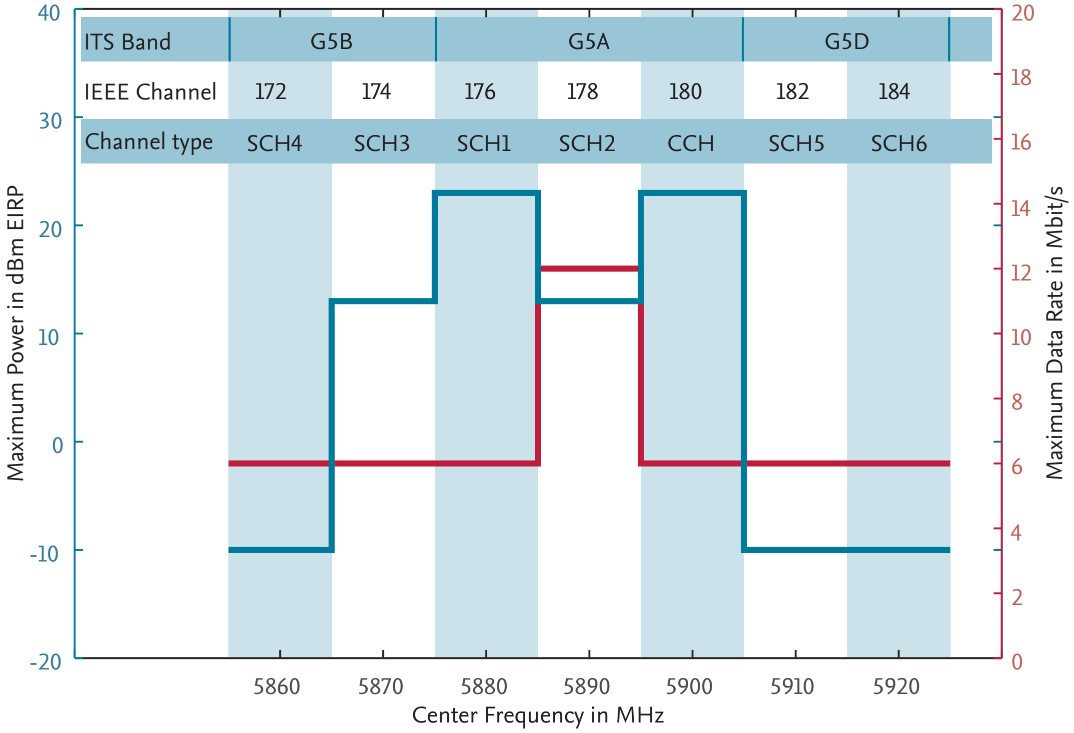


Figure 2.2.: ITS G5 Frequency Allocation [79]

efficiency. The remaining two SCHs between 5.905 GHz and 5.925 GHz make up the ITS G5D band and are allocated for future use [79]. Not displayed in Figure 2.2 is the ITS G5C band located between 5.470 GHz and 5.725 GHz, operating within the bandwidth which has also been allocated to other purposes, such as consumer wireless communication (e.g. IEEE 802.11 ac).

The ITS G5A, B and D bands are to be used outside the context of a Basic Service Set (BSS), whereas the ITS G5C band may only be used in conjunction with transmit power control and dynamic frequency selection mechanisms within a BSS [59]. Using the dedicated 5.9 GHz spectrum is license free, although specific power limits and spectrum masks have to be observed. Figure 2.2 also depicts the maximum mean spectral power densities as well as the data rates to be used in each channel.

Protocol Stack

As stated above, the ETSI is responsible for issuing standards regarding the employed protocols within the ITS G5 bands in Europe. Figure 2.3 depicts the ETSI ITS G5 reference architecture along with references to the most relevant related standards and other types of ETSI documents. The architecture consists of four horizontal layers related to the International Organization for Standardization (ISO) Open Systems Interconnection (OSI) model and two vertical protocol entities as displayed in Figure 2.3 [60, 245]. The following descriptions provide an overview of the relevant functionalities of each layer for this thesis.

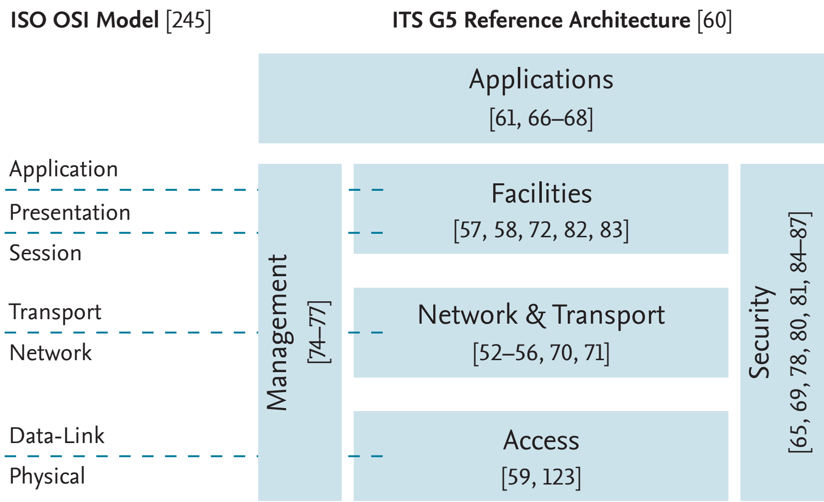


Figure 2.3.: ITS G5 Reference Architecture and corresponding ETSI documents

Access The Access layer employs Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and is based on the IEEE 802.11p standard with some additional restrictions regarding congestion control mechanisms [59]. The physical layer component is identical to the IEEE 802.11 PHY specification [123, Clause 18]. Data multiplexing is performed by employing Orthogonal Frequency Division Multiplexing (OFDM), due to its spectral efficiency and comparatively good performance for multipath interferences [175]. The data link layer component consists of the IEEE 802.11 Medium Access Control (MAC) and the IEEE 802.2 Logical Link Control (LLC) layers [123, 124]. Establishing an ad-hoc network between ITSs requires the nodes to operate outside of a BSS, i.e. authentication, association and synchronisation is deactivated. This is achieved by activating the MAC-Management Information Base (MIB) variable `dot11OCBActivated` [59]. On the MAC layer, messages to be sent are enqueued into four different Enhanced Distributed Coordination Access (EDCA) queues — a mechanism which allows for Quality of Service (QoS) guarantees by utilising different Arbitrary Inter Frame Space (AIFS) times with respect to the utilised queue [51, 59]. The LLC header, used to differentiate protocol operations on the MAC layer [122], is set to the unacknowledged connectionless mode and the Subnetwork Access Protocol (SNAP) header to the corresponding ether-type *0x8947* as specified in [55]. The maximum MAC Service Data Unit (MSDU) of 2304 Bytes restricts the maximum message size [123, Clause 5.2.2.2]. A unique addition of the European stack to the otherwise adapted IEEE standards of the Access layer is the requirement for Decentralised Congestion Control (DCC) mechanisms which are detailed below in subsection 2.1.4.

Network & Transport This layer introduces the unique *GeoNetworking* protocol which encompasses four different message dissemination schemes. Resulting from different requirements of IVC applications, the GeoNetworking header includes geographical information which enables dissemination to or within specific geographic boundaries [134]. Using the *Geographical Unicast (GeoUnicast)* scheme, a destination area is encoded in the header. Messages transmitted with this scheme might propagate over several hops until the destination is reached. Nodes forwarding these messages choose the next hop depending on the shortest distance to the destination. The *Geographically-scoped Broadcast (GeoBroadcast)* scheme is a similar mode except messages are being re-broadcast by any vehicle within the defined destination area. The more common dissemination scheme is the *Topologically-scoped Broadcasting* scheme, where the message is broadcast until a pre-defined hop-limit has been reached. Setting the hop-limit to one (i.e. a Single Hop Broadcasting (SHB)) therefore refers to broadcasting a message to all other nodes within the transmitter's communication range without retransmitting the message upon reception. The *Geographically-scoped Anycast (GeoAnycast)* scheme aims at delivering a message within a geographical target region, using several hops if necessary. In contrast to the unicast scheme, the addressee is unknown to the transmitting vehicle. As soon as the message arrives in the target area, it is not forwarded to other nodes in the same area [26, 52].

In order to support different communication media, the GeoNetworking protocol consists of *media-independent* [55] and *media-dependent* [70] functionalities. The former specifies the header formats depending on the selected dissemination mode. Figure 2.4 depicts the general structure of an ITS G5 packet. The GeoNetworking header consists of a mandatory *Basic Header* (4 Bytes) and a *Common Header* (8 Bytes) as well as of an optional *Extended Header* (up to 48 Bytes) data frame. The *Basic Header* essentially contains geographical information about the disseminating ITS-S. The *Extended Header* adds geographical information concerning the packet destination, e.g. for the GeoUnicast or the GeoAnycast schemes. In case ITS G5 is used as the communication medium, the latter *media-dependent* functionalities specify header fields for additionally sharing congestion control information (see subsection 2.1.4) and for service announcements on different ITS G5 bands [70]. If the security envelope is used within the message, only the *Basic Header* is located outside of the security payload.

Although other packet structures, such as IPv6 packets, are supported as well [71], the preferred transport protocol to be used in conjunction with the GeoNetworking protocol is the so-called Basic Transport Protocol (BTP) [56]. In close resemblance to the User Datagram Protocol (UDP), BTP focuses on multiplexing data from different services between ITS-Ss. The lightweight connectionless protocol adds an overhead of 4 Bytes and employs the concept of *ports* which are mapped to specific applications within the ITS-S.

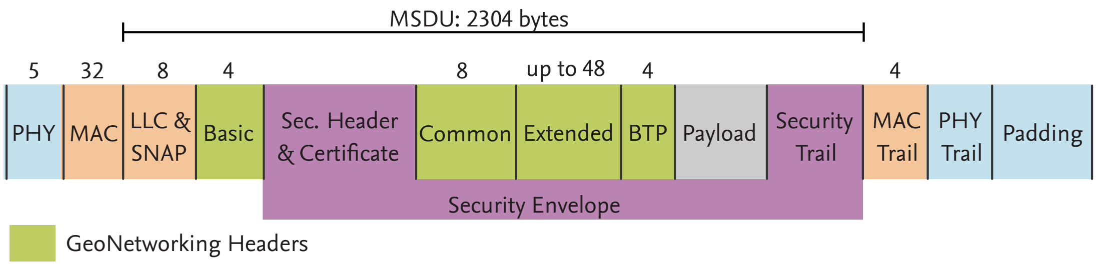


Figure 2.4.: General ITS G5 packet structure and header overhead

Two different header types are defined within BTP: the BTP-A-type is used for interactive packet transport, where the source and destination ports are transferred. The BTP-B-type only conveys the destination port as well as a port information field [56].

Facilities The Facilities layer can be interpreted as the applications' interface to the communication stack. Four facility types are differentiated: the *Application Support Facility* contains functionalities to provide interfaces for the Human Machine Interface (HMI), time-synchronisation, etc. *Information Support Facilities* provide a common database which can be accessed by ITS-S applications. The Local Dynamic Map (LDM) is the key component of this facility type and provides a list of all other received ITS-Ss and their corresponding data [61]. On a side-note, *Collective Perception* may be interpreted as a contribution to the LDM by adding vehicles and obstacles perceived by other sensors. As part of the *Communication Support Facility*, information about the current congestion state of the communication channel and interfaces for passing messages to lower layers are provided. Security information and address management is provided by the *Management Facilities* [82]. The Facilities layer also offers access to the vehicle's bus-systems for providing information to the ITS applications.

As part of the *Application Support Facility*, the so-called Cooperative Awareness (CA) [57] and Decentralized Environmental Notification (DEN) [58] basic services have been specified. Both services are responsible for generating two of the most important messages, the CAM and the Decentralized Environmental Notification Message (DENM), within the ETSI reference architecture and will be detailed in subsection 2.2.1. When operating on infrastructure components, ITS G5 is also responsible for disseminating information about the current traffic light status as part of the Signal Phase and Timing (SPaT) message [126]. Detailed schematics of the road or intersection ahead may be disseminated by using the Map-message [126]. Further details about the content of these and other messages generated within this domain are out of the scope of this thesis.

Applications The ETSI also specified a so-called Basic Set of Applications (BSA) focusing on road safety, traffic efficiency and other domains [72]. The content of the messages generated by the aforementioned CA and DEN service are used as input to these applications. Three applications have been standardised for early ITS applications, albeit OEMs are free to develop additional custom applications using the information from these standard messages. The Road Hazard Signalling (RHS) application defines several hazardous situations (e.g. slow vehicles, wrong way drivers or adverse weather conditions) which shall be exchanged between vehicles in order to warn drivers approaching the hazard [66]. The service employs data received from the CA, DEN and other application support services in order to either detect hazardous situations and to generate an according message or to issue a warning to the driver. Similarly, the Intersection Collision Risk Warning (ICRW) specification presents the required data and conditions for both detecting a prospective collision at an intersection and warning the driver and others accordingly [67]. The Longitudinal Collision Risk Warning (LCRW) aims at warning drivers in case of prospective collisions with other traffic participants, e.g. due to unstable driving conditions or wrong-way drivers [68]. All of these standardised applications aim at warning and informing the driver about potential hazards. Active intervention in the vehicle dynamics by either steering or braking is not intended. Hence, these applications fall into the scope of *Driver Assistance* (SAE-level 1, see Table 1.1). However, with an increasing number of vehicles being able to communicate, the number of applications and services relying on IVC will increase. Future additional messages will also be able to assist automated driving, as outlined in section 2.3.

Management and Security These cross-layer entities provide different services to each of the layers presented above. The management entity provides a so-called Management Information Base (MIB) which is responsible for storing global communication stack parameters [74]. Several interface-standards define the data that be can accessed by the different layers [75–77]. Furthermore, services for congestion control and inter-layer communication are provided [241]. The security entity provides an intrusion management service, which is accessible by all layers [65, 80, 84, 86, 87]. Furthermore, the relevant headers and methodologies for pseudonym management and ITS-S authentication via certificates are provided [69, 81]. Investigations and a detailed presentation of ITS G5 related security is out of the scope of this document. A detailed survey about privacy and security aspects of IVC is provided in [47, 236].

2.1.4. Decentralised Congestion Control

As stated above, the European ITS G5 stack introduces the unique concept of Decentralised Congestion Control (DCC). The reception of broadcast messages within the VANET is unacknowledged and connectionless — which leads to a loss of information in case of packet collisions. With an increasing number of communicating ITS-Ss, the probability of packet collisions and therefore lost information increases. Although the CSMA/CA mechanism aims at providing fair channel access to all vehicles, the random back off procedures will increase channel access delays [229]. Furthermore, the hidden-node problem causes interferences at communication boundaries, resulting in transmission failures. The scalability of the employed MAC mechanism is therefore limited — especially in scenarios with a large number of vehicles located within each other's communication range [199].

ITS-Ss are expected to stay tuned to the G5-CCH at all times. This channel is assigned to safety applications and thus accommodates CAMs and other safety-related messages. All vehicles within range thus have to share the available capacity of the G5-CCH while usage of the remaining channels is optional so far. In dense traffic situations, recent findings show that the channel may already be overburdened by handling CAMs alone [48]. Hence, the ETSI imposes a DCC mechanism which tries to anticipate excessive network load and to take measures for keeping the channel load below predefined thresholds [73]. Realisation of DCC is a cross-layer topic with entities located at the three horizontal and the cross-functional management entity. The following descriptions outline the distribution of DCC entities across these layers [64]. Depending on the employed DCC mechanism, only some of these entities are used. Vesco et al. state some of these mechanisms, such as altering the transmit power per packet, manipulating the rate at which ITS-Ss are allowed to transmit packets or adapting the data-rate dynamically [229].

Access layer DCC entity The DCC entity located at the Access layer is responsible for assessing the current channel utilisation. For this purpose, it provides the main metric employed by the envisioned DCC mechanism: the so-called Channel Busy Ratio (CBR). Essentially, the CBR is an expression of the relative channel utilisation over the last 100 ms. Whenever the channel is busy, as any vehicle is transmitting a message, the CBR increases according to the transmission duration. A more detailed description concerning the assessment of the CBR is provided in subsection 6.4.3.

The Access layer also provides a gatekeeper functionality by prioritising and enqueueing packets into four separate DCC queues, which are mapped onto the four EDCA queues as specified by the IEEE 802.11p standard [64, 123]. Dequeuing is performed by the flow control component of the gatekeeper, depending on the employed DCC algorithm. Once the packet has been dequeued, it is passed on to the ITS G5 radio, along with an information about the required transmit power. If the lifetime of an enqueued message expires, it is dropped within the access layer and the DCC component of the cross-functional management entity is notified accordingly.

Network & Transport layer DCC entity Whenever messages are either sent or received, they have to pass the Networking & Transport layer in order to process the GeoNetworking protocol headers, as stated above. Upon receiving a SHB ITS G5 message, the DCC entity in this layer extracts the relevant DCC parameters provided by the disseminating ITS-S within the GeoNetworking protocol's *extended* header. The *DCC Multi Channel Operation (MCO)* field within this header contains the so-called *CBR_L_0_Hop* and *CBR_L_1_Hop* measurements as well as the output power of the received packet [70]. *CBR_L_0_Hop* refers to the local CBR and is utilised to inform receiving vehicles about their locally perceived channel load. To provide information about the disseminating ITS-S's DCC limitations due to neighbouring DCC operations, *CBR_L_1_Hop* provides the highest received CBR measurement of the transmitting node. This information is stored in a *neighbour table* which may be accessed by the *CBR evaluation* entity of the Management layer.

Upon sending a SHB message, i.e. a message is passed from the Facility layer to the Networking & Transport layer, the local CBR measurements are extracted from the Management layer components and inserted into the GeoNetworking header, as described above. Furthermore, in case multi-channel operation is supported by the ITS-S, the Management layer is queried for DCC channel switching parameters.

Facility layer DCC entity Primary concern of DCC operations is to ensure the correct dissemination of the standardised messages, at least on the CCH. For this purpose, DCC focuses on performing *traffic shaping*, which consists of delaying, re-scheduling and dropping of packets if necessary. The two most important message types, the CAM and the DENM, have to be generated within certain limits for V2X applications to work properly, as detailed in subsection 2.2.1. Therefore, the DCC entity at the Facility layer controls the load generated by these two messages by providing specific DCC parameters which are obeyed by the message generation algorithms. The purpose of the DCC intervention at this layer is to prevent message delays or drops for these message types at the Access layer altogether. Furthermore, the Management DCC layer-components may be queried by Facility layer entities to provide information about specific DCC Profiles (DPs). These profiles are passed on to the lower layers upon message generation in order to control message enqueueing in one of the DCC queues [73].

Management layer DCC entity The DCC entity located at the Management layer is the connecting interface between the other layers. The *DCC Facilities* interface provides available channel resources specific to the entities of the Application and Facility layers. This information may be used by these layers for generating messages and for adapting generation frequencies and message sizes according to the available channel resources. The determination of the channel resource information depends on the employed DCC algorithm and is a function of the number of ITS-Ss located within communication range as well as of the resulting maximum CBR [64]. If applicable, the *DCC Networking & Transport* interface provides channel availability to be used for data offloading to channels other than the ITS G5-CCH. The *DCC parameter evaluation* component is the most important Management layer DCC entity and provides all internal DCC parameters which are distributed to the other layers. Based on the locally determined CBR of the *CBR evaluation* component and the global DCC RX parameters from neighbouring ITS-Ss, the provided global DCC TX parameters may be employed by the Networking & Transport layer as outlined above.

A more detailed simulation analysis of different DCC implementations in the context of *Collective Perception* is provided in chapter 6.

2.2. Environment Perception

Most of today's ADASs rely on available perception data from on-board sensors. An ACC system, for example, usually gathers information from a Radio detection and ranging (Radar) or Light detection and ranging (Lidar) sensor in order to maintain and control a pre-defined time-gap to the vehicle in front. One of the main purposes of vehicular communication is to enhance a vehicle's perception capabilities. Whereas local perception sensors require a LoS to the object to be perceived, wireless IVC also works in obstructed LoS conditions [158, 189, 194, 212]. Hence, from a perception point of view, V2X communication can be interpreted as an additional sensor. Furthermore, a direct communication link enables the exchange of information which cannot be obtained from an on-board perception sensor, such as a vehicle's mass or the number of passengers. Especially in the context of highly automated driving, a comprehensive understanding of a vehicle's surroundings is required. Different technologies contribute to this understanding to establish an environment model — which is the holistic, best effort knowledge base of a vehicle's immediate driving environment. The environment model can be accessed by all ADAS applications of a vehicle.

Figure 2.5 depicts the modules of an environment model schematically. The model distinguishes three separate driving contexts: the *Global Driving Context* is based on a

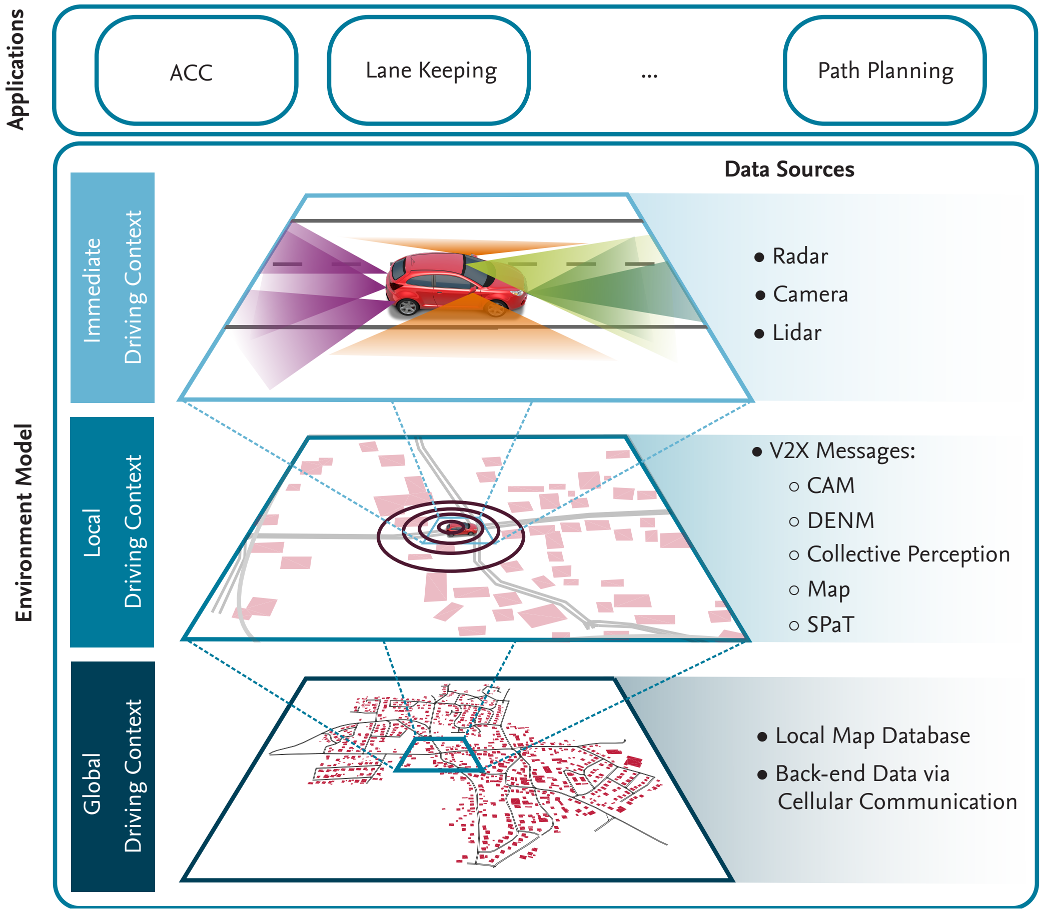


Figure 2.5.: Modules of an Environment Model

high resolution map of the driving environment of a vehicle. This data can be used for anticipatory path planning and mapping of context information, such as current traffic congestions and traffic light information [176]. Cellular communication contributes information to this module, e.g. by means of a connection to an OEM back-end [99, 216]. The *Local Driving Context* is primarily based on information gathered by means of V2X communication. CAMs and DENMs are used for gaining knowledge about the presence of other ITS-Ss and potential hazards within its vicinity. The concept of *Collective Perception* contributes local perception data received from other ITS-Ss to this context, as introduced in section 1.1. Additionally, information about the intersection ahead along with corresponding traffic light information are provided by the Map and SPaT message types. The *Immediate Driving Context* is based on the data gathered by the local perception sensors of the vehicle. The information provided by several sensor systems is fused to detect obstacles and objects located within the LoS of a vehicle.

Due to the underlying physical principles, on-board sensors gather information about the vehicle's environment *implicitly*, as information about objects can only be obtained by means of observation. V2X communication, however, *explicitly* contributes information to the environment model as the sender is responsible for providing the information itself.

Each module of the model is thereby more than a simple database: data received from other ITS-Ss or objects perceived by local sensors have to be matched to the map, e.g. attributes such as the current lane position have to be assigned to an object [242]. Furthermore, spatial and temporal alignment of the data maintained within the environment model has to be ensured. For this purpose, different measurement and update cycles due to reception data rates or sensor measurement frequencies have to be compensated by predicting and fusing data from different sources to the same object [16, 143, 198, 251]. Temporally aligned data from all modules is then made accessible to ADAS applications and the path-planning module of SDSs, as depicted in Figure 2.5.

Subsection 2.2.1 introduces the already standardised message formats encoding status information within a VANET. The working principles, as well as the data gathered of the two sensor types employed within this thesis are introduced in subsection 2.2.2.

2.2.1. V2X as a Sensor

Vehicles equipped with V2X communication technology are enabled to directly exchange information with other communicating traffic participants. Hence, V2X communication contributes information to the environment model of a vehicle just like on-board sensors do. Within the European ITS G5 framework, several message formats have been standardised for exchanging information between ITS-Ss. Two mechanisms have to be differentiated: the *awareness-based* mechanism focuses on cyclically notifying surrounding communication partners about their presence, by disseminating Cooperative Awareness Messages (CAMs). In the context of the *event-based* mechanism, a Decentralized Environmental Notification Message (DENM) is sent, whenever an abnormal traffic or driving situation has been detected. The following paragraphs provide more details for both message types.

CAM The periodically disseminated Cooperative Awareness Message (CAM) contains relevant status information about the disseminating ITS-S. The formal Abstract Syntax Notation One (ASN.1) specification as well as the dissemination parameters are provided as part of the CA service which is located within the Facility layer of the ETSI ITS G5 reference architecture [57]. The main purpose of the CAM is the notification of other ITS-Ss about the presence of the transmitter. Hence, several information are encapsulated within the message, which has to be sent as a SHB on the G5-CCH and which is encoded using ASN.1 Unaligned Packed Encoding Rules (UPER). Based on the requirements of the standardised applications in the Application layer [66–68] and with the intention of keeping the resulting channel utilisation within limits, the message generation frequency is adapted dynamically between 1 Hz and 10 Hz [57]. Within these limits, a CAM shall be generated whenever one of the following conditions applies:

1. The ITS-S changes its heading, i.e. its orientation within the World Geodetic System of 1984 (WGS84) coordinate system by more than 4°, compared to the last transmitted CAM.

2. The absolute distance between the current ITS-S's position and the one transmitted in the last CAM exceeds 4 m.

3. The current velocity of the ITS-S exceeds the velocity value sent in the last CAM by more than 0.5 m/s.

Additionally, *traffic shaping* may be performed by the DCC mechanisms by adjusting the time between consecutive CAMs [57].

As for any ITS G5 message, the CAM consists of several separate data containers, which themselves represent a collection of variables which are mostly defined in a Common Data Dictionary (CDD) [83]. Figure 2.6 outlines the basic structure of the message, along with the corresponding variables of each container. The complete encoded message represents the payload of an ITS G5 packet, as depicted in Figure 2.4.

The mandatory *ITS PDU Header* contains information about the employed protocol, the message type and the unique ID (current pseudonym) of the disseminating ITS-S. The type of the disseminating ITS-S as well as its latest available geographic position, consisting of latitude, longitude and altitude are provided as part of the mandatory *Basic Container*. Depending on the station type of the disseminating ITS-S, different mandatory *High*

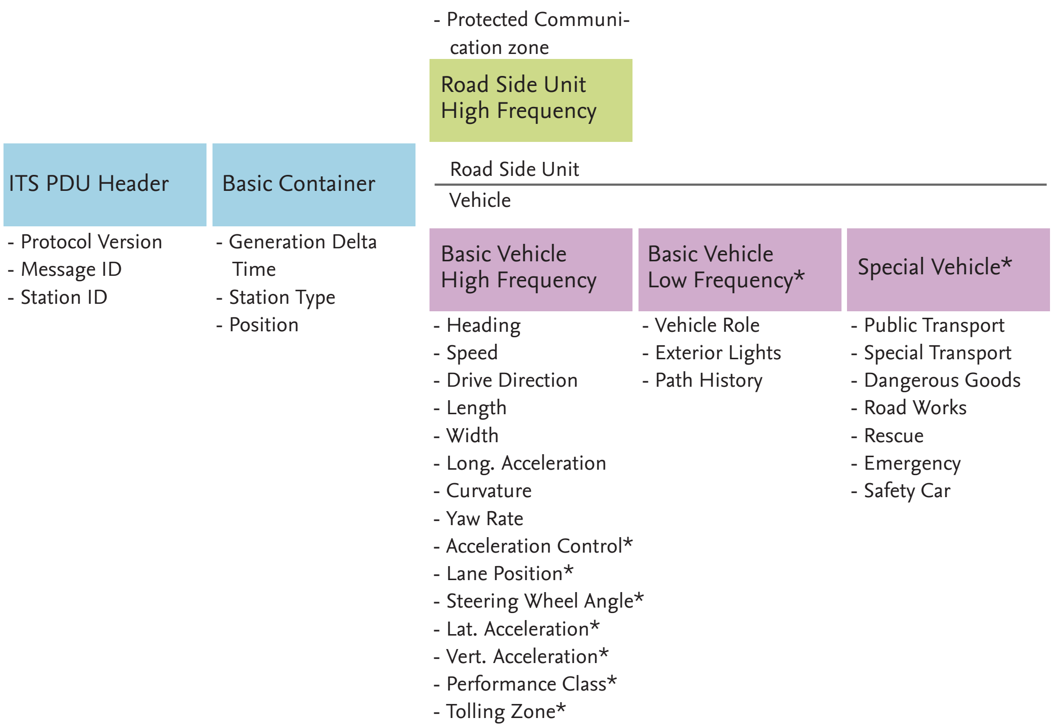


Figure 2.6.: Cooperative Awareness Message Structure. (*) indicate optional variables [57]

Frequency Containers are added. Roadside Units (RSUs) add a specific container restricting the use of ITS G5 within tolling zones also employing DSRC. Vehicles, however, add the *Vehicle High Frequency Container* which contains, amongst others, dynamically changing status information such as the current speed, the heading within the WGS84 coordinate system and the yaw rate. Furthermore, this container also contains optional variables, such as the current lane position and the current steering wheel angle which may only be added if applicable. Optional variables are a mechanism for reducing the resulting message size — which in turn also reduces the required air-time and hence the channel utilisation due to the transmission. Therefore, the optional *Low Frequency Container* is only added every 500 ms. It contains the role of the vehicle within traffic (e.g. public transport, emergency vehicle, etc.), the status of the exterior lights, as well as a so-called *path history*. The former is a collection of up to 23 points outlining the past movement of the ITS-S with respect to the current position. ITS-Ss with a special role within traffic, e.g. emergency or public transport vehicles, additionally have to add a *Special Vehicle Container* every 500 ms. This container indicates, for example, whether a siren or light-bar is in use, or whether passengers are currently embarking a public transport system.

DENM Contrary to the CAM, the Decentralized Environmental Notification Message (DENM) is an event-triggered message which is used for describing abnormal traffic situations and road hazards. Like the CAM, the message is generated within the Facility layer of the ITS G5 reference architecture as part of the DEN basic service [58]. Whenever an ITS-S detects one of the standardised abnormal traffic events, a message describing the event will be disseminated. As notifications about these events may be of interest to ITS-Ss which are located outside of the current communication range, DENMs may be forwarded by other ITS-Ss. In general, four different DENM types have to be differentiated: a *new DENM* will be sent, whenever an ITS-S detects one of the specified abnormal events. The ITS-S provides a unique action ID to the message, which is a combination of the originating station ID and a sequence number. Whenever the situation or event that caused the dissemination of the initial DENM changes, an *update DENM* may be generated by the same ITS-S. A *cancellation DENM* will be sent by the same ITS-S, whenever the event causing the initial DENM became obsolete. Whereas these three DENM types may only be sent by the ITS-S which initiated DENM transmission for this event, a *negation DENM* may be sent by other ITS-Ss as well. This message type may be used in case another ITS-S cannot confirm the existence of the event any more. DENMs are not subjected to DCC regulations on the CCH. Hence, they are given a higher priority and will be favoured for transmission over CAMs and other message types.

As some events may only be of interest to specific ITS-Ss, e.g. a slippery road on only one side of a highway, the DEN basic service makes use of the *extended header* of the GeoNetworking protocol. By providing information about the relevance area of the DENM, forwarding ITS-Ss may relay the message without having to decode its content. What is more, the DEN service offers a keep-alive forwarding functionality, maximising the spread of the message: a DENM may be stored by any receiving ITS-S, as long as it is valid and the station is located within the relevance or destination area of a DENM.

As for the CAM, ASN.1 UPER are used for encoding the message. The basic structure of the message, along with a brief overview of the relevant message content is provided in Figure 2.7. The *ITS PDU header* is identical to the one used in the CAM in order to identify the protocol format and the originating ITS-S. The validity duration and geographical relevance information is provided as part of the *management container*. The following three optional containers describe the specific events encoded as part of the DENM. The *situation container* provides information about the event type, as detailed in [58]. Up to 24 cause codes with several sub-states allow for the description of the specific event, e.g. traffic conditions, accidents, roadworks and adverse weather conditions. If applicable, the *location container* details the dynamic properties of the event, e.g. the speed and heading in case of an emergency vehicle. Information specific to an event, such as more details about road works or stationary vehicles may be provided as part of the *à la carte container*.

2.2.2. Local Perception Sensors

A multitude of perception sensors are available even for today's vehicles. These sensors are mounted on different positions of the vehicle to contribute to an extensive representation of the vehicle's *immediate driving context*, as depicted in Figure 2.5. Front-facing sensors, such as Radar, Lidar or camera devices are mainly used for applications such as ACC,

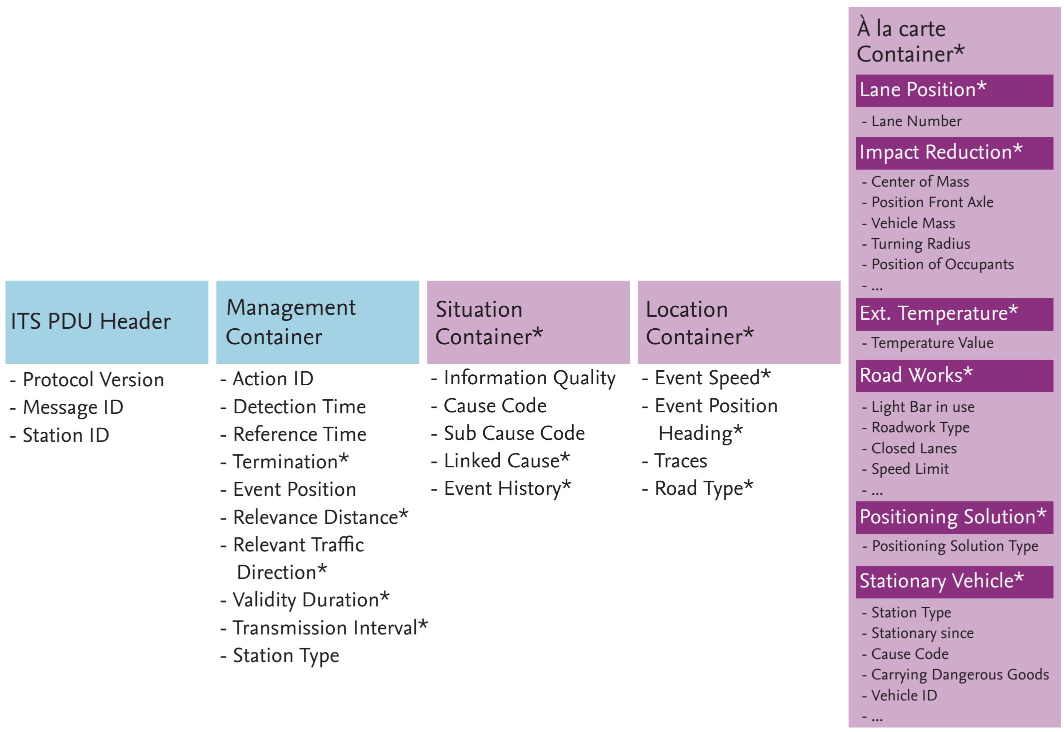


Figure 2.7.: Decentralized Environmental Notification Message Structure. (*) indicate optional variables [58]

forward collision warnings and lane keeping systems. Side- and rear-facing sensors are used for lane-change assistance and for the detection of vehicles located within the driver's blind-spot [9, 243]. Rather than exchanging the current decision of an ADAS application, *Collective Perception* aims at exchanging the data gathered from these sensors in order for ADAS applications on a receiving vehicle to employ the data in its logic as well.

Two different sensor types have been employed as part of this thesis. Hence, the characteristics and working principles of these sensors are outlined below.

Radar Sensor Radio detection and ranging (Radar) sensors were amongst the first local perception sensors to be found on road vehicles. The first application for which this sensor has been installed is the ACC which has been mentioned above [243]. The working principle of the Radar sensor is based on modulated electromagnetic waves which are reflected by objects within the sensor's lobe. Automotive Radar sensors may operate in three different frequency bands, ranging from 21.65–26.65 GHz, 24–24.25 GHz and 76–77 GHz [243]. The relative velocity of an object $\dot{r}_o$ can be derived from the reflected electromagnetic wave due to the Doppler effect. A received signal $u_c(t)$ of frequency f_0 can be rewritten as depicted in Equation 2.1, where A_c, λ, ϕ_c are the amplitude, wavelength and phase of the carrier signal:

$$u_c(t) = A_c \cdot cos(2\pi(f_0 - 2\dot{r}_o/\lambda)t + \phi_c). \tag{2.1}$$

With a relative velocity between the sender and the reflecting object, the resulting change in frequency can be described by the so-called *Doppler-frequency* f_{Doppler} which is found to be

$$f_{\text{Doppler}} = 2\dot{r}_o/\lambda. \tag{2.2}$$

The *Doppler frequency* scales proportionally with the frequency of the carrier signal. Radar sensors operating between 76–77 GHz ($\lambda \approx 0.003$ m), for example, experience a *Doppler frequency* of about 510 Hz $\cdot\, \dot{r}_o$ [243]. Various types of Radar sensors have to be differentiated: pulse modulated Radars cyclically emit a characteristic carrier signal for a certain pulse length t_p, whereas frequency modulated Radars continuously vary the frequency f_0 of the carrier signal. For pulse modulated Radars, the distance to the object d_{O} reflecting the electromagnetic wave can be calculated due to knowledge of the speed of light c_l and the time difference Δt between the emission and the reception of the reflected modulated signal:

$$d_{\text{O}} = \frac{1}{2} c_l * \Delta t. \tag{2.3}$$

For frequency modulated Radars, determination of the distance depends on the measurement of the difference between the current and the reflected signal frequencies [243].

However, knowledge about the (radial) distance and relative velocity of an object is not sufficient for ADAS applications. Detected objects can only be used by these applications

Table 2.1.: Specifications of Radar sensors used within this thesis [40, 188, 243]

Property	**Bosch LRR 3**	**Delphi ESR**
Frequency Range	76–77 GHz	76–77 GHz
Measurement cycle	<125 ms	50 ms
Range and accuracy	0.5–250 m, ±0.1 m	LR[1]: 1–200 m, ±0.5 m MR[2]: 1–60 m, ±0.25 m
Relative speed and accuracy	−75 to 60 m/s, ± 0.12 m/s	LR: −100 to 25 m/s, ± 0.12 m/s MR: −100 to 25 m/s, ± 0.12 m/s
Horizontal Opening Angle	30°	LR: 10° MR: 45°
Angle measurement principle	4-lobes with phase difference determination	Digital Beam Forming
Maximum number of objects	32	64

1) LR: Long Range
2) MR: Mid Range

correctly, when the angular orientation of the distance and velocity vector with respect to the measuring vehicle is known. Several mechanisms for determining the angle to the measured object exist: *scanning Radars* physically pan a Radar antenna with a small azimuth over the measurement area. The measured power of the reflected signal is assigned to the antenna position over time in order to determine the angular position of the object. *Monopulse Radars* employ three separate antennas, whereas only the centre antenna is used for transmission. With knowledge about the distance between the two reception antennas, a phase difference for the received signal can be related to the angular position of the measured object. However, multiple detected objects may lead to ambiguities. Rather than using two reception and one transmission antenna, *multi-transmit Radars* employ several antennas for transmitting the carrier signal. By comparing the received signal strength of the reflected modulated carrier signal with the antenna characteristics, the angular position of a detected object is determined [243]. *Dual sensor* systems use two separate Radar sensors mounted on each side of the vehicle. Next to the larger coverage area, the determination of the azimuth angle can be improved [148].

The characteristics of the sensors used for the implementation of *Collective Perception* within a vehicle, as described in chapter 7, are detailed in Table 2.1. The Bosch Long Range Radar (LRR) sensor employs frequency modulation with four separate Radar lobes for one measurement area, whereas the Delphi Electronic Scanning Radar (ESR) combines a long and mid range Radar for two combined measurement areas with different characteristics.

Lidar Sensor Light detection and ranging (Lidar) sensors are essentially based on the same measurement principles as Radar sensors but differ in terms of their employed carrier signal [243]. Rather than using millimetre or sub-millimetre wavelengths, infrared or visible light is used by this type of sensor. Measuring the distance to detected objects is performed with a simple time-of-flight measurement. For this purpose, pulsed light is emitted from the sensor. The time from emitting the signal to reception of the reflection is then used as detailed in Equation 2.3 for determining the distance to the detected object. The expected reflection follows a Gaussian distribution with different characteristics based on the attenuation of the carrier signal. Fog and drizzle cause multiple reflections and hence a different (wider) shape of the Gaussian distribution of the received signals. By adapting the receiver sensitivity, however, these weather conditions can be detected. As for Radar sensors, the Doppler effect may be used for determining the relative velocity of detected objects. However, due to challenging hardware requirements for measuring Doppler-frequencies within the spectrum of visible light, the relative velocity of the object $\dot{r_o}$ can be determined quite accurately by differentiating two consecutive distance measurements d_o:

$$\dot{r_o} = \lim_{\Delta t \to 0} \frac{\Delta d_o}{\Delta t} \tag{2.4}$$

Lidar sensors typically emit pulsed signals with a wavelength between 850 nm and 1 μm. Usual pulse lengths lie within the order of 30 ns [243]. Sensor accuracy, however, is determined by the reception sensitivity. Due to the very short times-of-flight for close objects, high measurement speeds need to be ensured. Additional challenges arise due to wavelengths of day-light also located within the infrared region. Furthermore, the working environment of the sensor plays a crucial role for its capabilities. Different transmission characteristics of the propagation medium have further effects on the accuracy of the measurements. As the signal is attenuated due to absorption, scattering, deflection and reflection, only a fraction of the emitted signal is available for the actual measurements. Furthermore, most objects – and especially bodies of vehicles – exhibit a diffuse reflection image, where the reflected signal is distributed homogeneously, resulting in less than 20 % of the pulsed signal to be reflected. Due to restrictions regarding the allowed transmit power of Lidar sensors, ray-bundling may be used for increasing the power density. However, bundled rays cause total reflection on plane surfaces which cannot be detected by the sensor. Hence, wider or multiple light beams are used in combination with increased receiver sensitivity [117].

Opposed to Radar sensors, Lidars offer several additional functionalities which are helpful for ADAS applications. Current FoVs and hence free areas within the vicinity of

Table 2.2.: Specification of the Lidar sensor used within this thesis [121]

Property	**Valeo Scala**
Wavelength	905 nm
Horizontal Field-of-View	110°
Vertical Field-of-View	3.2°
Number of vertical layers	4, each of 0.8°
Range and accuracy	200 m ± 0.1 m
Maximum number of objects	65

vehicles can be determined. Furthermore, due to detection of standstill objects, the velocity of the host-vehicle can be estimated as well. The high resolution of the sensor also allows estimates of object geometries (length and width) as well as of their relative orientation (yaw-angle) with respect to the measuring vehicle.

Table 2.2 details the specification of the employed Lidar sensor for the implementation of *Collective Perception* within a vehicle.

2.3. Collective Perception and Cooperative Driving

Exchanging sensor data between vehicles not only increases their mutual perception capabilities for other traffic participants — it also represents a crucial step towards realising *cooperative* behaviour of future SDSs. This thesis is part of a holistic approach for researching design principles of *Cooperative Driving*. As such, the following sections introduce the related work and emplace the concept of *Collective Perception* in the context of *Cooperative Driving*.

2.3.1. The Concept of Cooperative Driving

Drivers of today's vehicles already cooperate with each other in traffic — either directly or indirectly. The term *cooperation* within the context of road traffic, however, is subject to different interpretations. Düring et al. propose a framework for determining the degree of cooperation within a certain driving context. For this purpose, the authors propose seven properties of cooperative behaviour [46]. Figure 2.8 depicts how cooperative behaviour can be determined. The essence of cooperation, however, is the requirement of at least two agents with separate utility functions u_1 and u_2.

Whenever the total utility increases, the behaviour of each agent can be described as being cooperative. From the position of the first agent, *egoistic* behaviour increases its own utility, whilst maintaining the utility of the other agent. *Altruistic* behaviour, however, increases the other agent's utility, whilst maintaining the first agent's utility. As long as both agents' utilities are increased, their behaviour is *rationally cooperative*. An example for rational cooperative behaviour may be one vehicle waiting for another vehicle to reverse out of a parking space in order to park in the same space afterwards. *Altruistic cooperative* behaviour is exhibited whenever one agent decreases its own utility in favour of the other agent's utility. In the reverse manner, agents exhibiting *egoistic cooperative* behaviour increase their own utility at the cost of the other agent's utility. Each of these behaviours, however, is cooperative, as overall utility is increased. Any (combined) behaviour decreasing the overall utility is hence considered as being *uncooperative* [46].

With increasing levels of automation, vehicle applications and other traffic participants need to agree on a common understanding of what each participant in a current driving scenario is allowed to do for not to decrease the overall utility. Even further, automated vehicles need to rely on a common understanding of *cooperation*, for them not to cause pervasive unfairness within traffic. Hence, Pascheka et al. extend their earlier work by assigning expenditure according to a cost-function to certain driving manoeuvres [170].

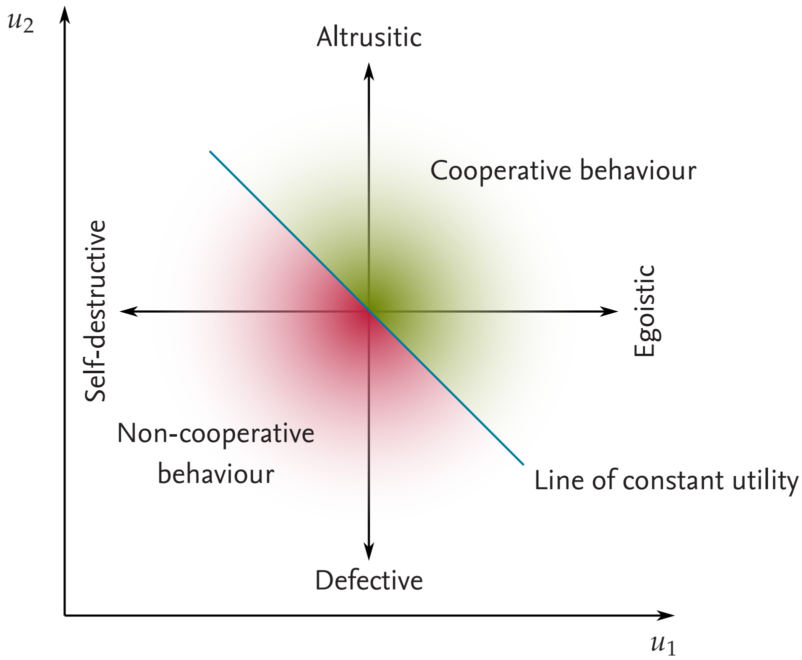


Figure 2.8.: Cooperative behaviour, adapted from [46]

Furthermore, the agents have an associated long-term cost memory which is considered for any decision making process.

Based on these considerations, Franke et al. propose a reference architecture for so-called Cooperative Driver Assistance Systems (CDASs) [95]. Figure 2.9 depicts a slightly

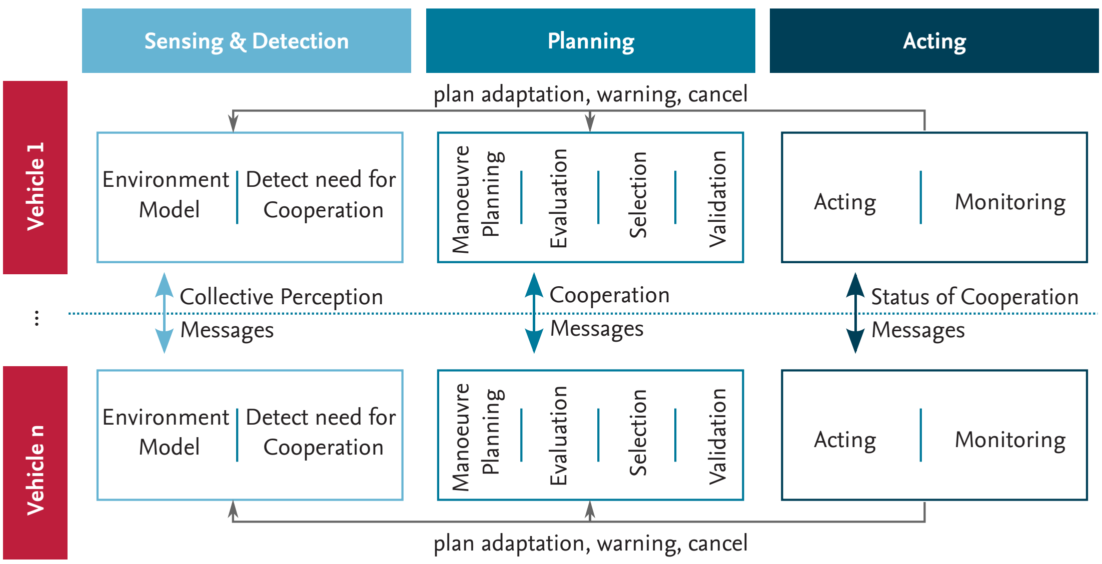


Figure 2.9.: Reference architecture for Cooperative Driver Assistance System, adapted from [95]

adapted architecture for CDASs, consisting of three main components closely resembling the human approach towards resolving traffic situations. The *Sensing and Detection* phase is responsible for continuously collecting information about a vehicle's environment. For this purpose an environment model, as depicted in Figure 2.5, is maintained by each vehicle. This model updates its information with the help of the vehicle's local perception sensors and data received from other vehicles or infrastructure facilities via IVC. As part of this module, *Collective Perception* is responsible for sharing locally perceived objects between vehicles. Whenever a vehicle application detects a situation which requires coordination between itself and other vehicles, Franke et al. propose sending a corresponding Request for Cooperation Message (RCM) [95]. The *Planning* phase is entered, whenever an RCM has been sent. All cooperating agents generate, evaluate and select a mutual collision free manoeuvre which is shared and confirmed by agents [95]. The authors also propose different message types for exchanging the data inherent to the decision process. Once all agents agreed upon a common manoeuvre, the *Acting* phase is responsible for following the common plan. However, deviations from this plan may occur, e.g. due to a suddenly appearing obstacle on the road. For this purpose, the *Acting* phase encompasses a monitoring facility which is detailed in [11]. Within a vehicle, this triad is performed continuously and is therefore designed as a closed control loop, where plan adaptations can be performed.

2.3.2. Levels of Cooperation

Whilst the reference architecture outlined above emplaces *Collective Perception* within the context of *Cooperative Driving*, the technology may not only be employed exclusively within this context. Furthermore, *Cooperative Driving* is by no means limited to automated driving systems only. Whilst next generation vehicles will be increasingly equipped with hardware and software rendering automated driving applications feasible, *Collective Perception* will also be beneficial for partially automated systems. Hence, Figure 2.10 introduces different levels of cooperation which are mapped on corresponding SAE levels for automated driving systems, as listed in Table 1.1.

Within the proposed model, two stages are differentiated. The two lower layers contain descriptive information about the status and the environment of a vehicle. This information is retrospective in the sense that it merely describes the last states of the vehicle and its environment up to the current point in time. The top layers, in turn, provide information dedicated to improve the quality of predicting the behaviour of the traffic participants by means of exchanging information about their future (driving) behaviour. The phrases in each box in Figure 2.10 illustrate the extent of cooperative behaviour for each level from the driver's perspective.

The *status information* layer builds the foundation of the architecture and consists of messages and functionalities intended solely for exchanging each other's status information. With the market introduction of V2X communication, these functionalities are based on the legacy messages such as the CAM, DENM and alike [58, 83, 126]. These messages provide status information about their sender only. Even today's ADAS applications (SAE level 1) may benefit from this information as input to their algorithms. As a next step,

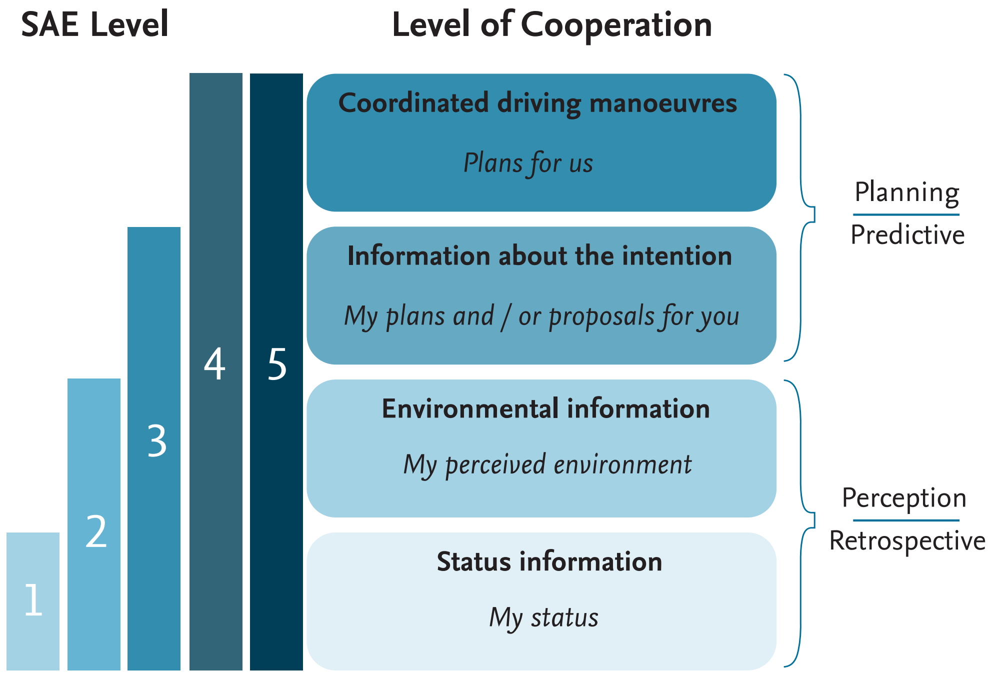


Figure 2.10.: Classification of cooperative systems

cooperative systems exchange *environment information* to increase their mutual awareness of the environment. Located at the core of this level is the concept of *Collective Perception* which is developed as part of this thesis. This layer incorporates all means of increasing the horizon of perception by utilising the perception facilities of others. SAE level 1 and 2 applications may use this data to issue warnings to the drivers. Additionally, conditional automated driving systems (SAE level 3) may rely on shared sensor data for long-term path planning and for performing obstruction checks. The two lower layers describe the current driving situation without predicting or exchanging each other's behaviour.

However, the driving behaviour can be influenced explicitly, by notifying others about their intentions and future plans. This *information about the intention* layer can be employed by others to improve the quality of predicting the behaviour of traffic participants and to adapt their own behaviour accordingly. Agents will exchange their future behaviour and notify others about plan alterations. The long-term goal of *coordinated driving manoeuvres* requires an additional set of messages to reach agreements on the mutual behaviour in a certain traffic situation, as detailed in subsection 2.3.1. High and fully automated driving systems (SAE level 4 & 5) will be able to perform the full dynamic driving task — even in hazardous situations as requested by the SAE [211].

3 Methodology

The principle of *Collective Perception* represents a key technology towards the realisation of novel cooperative systems in the automotive context, as outlined in the previous chapters. The objective of this thesis is the development of a holistic concept for this principle.

Within this thesis, ETSI ITS G5 is used as the principal communication technology for exchanging sensor data between vehicles. Different requirements regarding *Collective Perception* result from different perspectives. At the core of the concept is a mechanism for exchanging sensor information between communicating traffic participants. The foundation for the development of *Collective Perception* is provided by analysing existing related work, as presented in chapter 4. From an inter-vehicle network point of view, several limitations arise from the employed protocol stack itself. These limitations influence the development of the prospective messages and the corresponding message sizes as well as the generation rules. Hence, the *Macroscopic Analyses* presented in chapter 6 focus on network related factors. From the perspective of ADASs, however, there are certain requirements regarding the actual content (e.g. data fields) to be exchanged. Furthermore, the environment model of a vehicle requires frequent updates of perceived objects to keep prediction errors within limits. Hence, the *Microscopic Analyses* detailed in chapter 7 provide insights to the realisation of *Collective Perception* within an actual vehicle. Rather than focusing on the effects of the interaction between vehicles on the network, the chapter demonstrates the capabilities of the concept as part of a collision avoidance application for two automated vehicles. As depicted in Figure 3.1, the findings of either perspective influence the development of the message format of *Collective Perception*, which also effects the findings of the other perspective. The developed message formats take these various requirements into account and are presented in chapter 5.

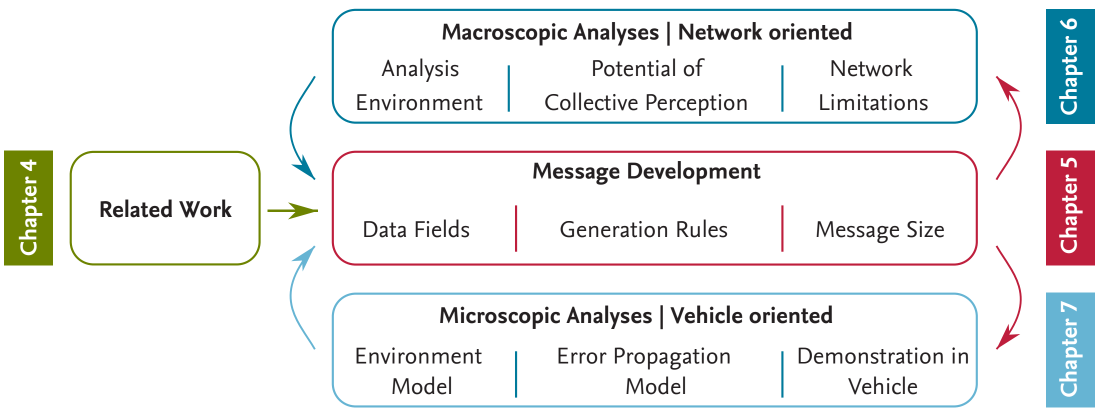


Figure 3.1.: Research areas of *Collective Perception*

The following sections introduce the research questions addressed by this thesis. References to corresponding publications are provided, whenever applicable.

3.1. Macroscopic Analyses

As stated above, the communication between vehicles is based on the European ITS G5 communication architecture [60]. Therefore, any new technology and extension, such as the principle of *Collective Perception*, has to comply with the restrictions of this architecture. The more vehicles are located within each other's communication range, the higher the observed channel utilisation. Hence, different mechanisms for keeping the channel utilisation within limits have to be investigated.

Consequently, the first task of the macroscopic network-oriented analyses is the development of a framework for in-depth investigations of the protocol stack in dense traffic scenarios. The basis for any network-related analysis is therefore a holistic simulation environment which not only simulates the complete protocol stack for each network node but also provides realistic node movements somewhat resembling vehicular traffic. Next to the protocol stack, the analysis of *Collective Perception* requires these nodes to be also equipped with local perception sensors in order to provide realistic input data for the message formats developed in chapter 5. For this purpose, chapter 6 introduces several extensions to an existing simulation framework.

From here, the following research questions will be addressed:

What is the potential of *Collective Perception*?

- As indicated in section 1.1, V2X communication is subjected to the *Network Effect*, i.e. a certain amount of users — the critical mass — is required for the technology to be accepted by customers. *Collective Perception* aims at reducing the required critical mass by publishing non-V2X-enabled vehicles in the network as well.

- To reveal the potential of *Collective Perception*, a traffic simulator is coupled with a network simulation framework in section 6.2. This framework is then employed to determine the additional number of vehicles published within the network by means of exchanging sensor data in section 6.5. These findings are compared to equivalent scenarios, in which communicating ITS-Ss only exchange information about themselves, as it is the case for legacy V2X enabled vehicles (day 1). The simulations are performed for different market penetration rates of V2X communication technologies to determine the required critical number of users for the technology to be effective.

- **Publications:** The simulation framework *Artery* is introduced in [183]. Dedicated towards the analysis of applications and facilities within the ITS G5 stack, the simulation framework is the basis for the network oriented analyses. Amongst others, [105] extends this framework with local perception sensors which can be attached to vehicles within the simulation. The work presented in [108] employs this simulation framework to study the potential of *Collective Perception*.

Which limitations for *Collective Perception* result from the employed ETSI ITS G5 protocol stack?

- The communication stack has to provide several mechanisms to cope with the challenges of IVC scenarios. The highly dynamic topology of mobile ad-hoc networks and the varying number of communication partners from just a few nodes, up to several hundred nodes in traffic jams and dense cities are only some of these challenges. To ensure communication for every vehicle in the network, these mechanisms aim at controlling the amount of data to be transmitted, as well as at reducing the channel access times of each node. Therefore, the stack provides DCC mechanisms influencing the message generation rules and dissemination frequencies [25, 88].
- As part of this research question, the capabilities of an ITS G5-based communication network regarding the introduction of an additional message type have to be analysed. For this purpose, a trade-off between the analytical requirements of prediction models employed within an environment model and the capabilities of the ITS G5 communication stack will be considered in section 6.6. Additionally, the messages to be exchanged should be able to *breathe*, i.e. change in size and therefore vary by the amount of data conveyed with respect to the current utilisation of the communication channel. As a result, DCC specific requirements have to be considered, when designing messages in the context of sharing sensor data between vehicles.
- **Publications:** An analysis of different message formats for realising *Collective Perception* is presented in [104]. The work also shows the network limitations due to different DCC mechanisms.

3.2. Microscopic Analyses

The findings of the network-oriented analyses outlined above influence the research for the vehicle oriented implementation and the message formats of *Collective Perception*. From the perspective of a VANET, the content of the message is irrelevant, as long as the message size, which ultimately influences the channel utilisation, can be modelled accurately. However, to be able to correctly transform and fuse perceived objects from another vehicle's reference frame into the receiving vehicle's reference frame, the information conveyed in the message is essential. Therefore, primary objective of the *Microscopic Analyses* is to identify the required variables from the perspective of an ADAS application. Albeit *Collective Perception* does not represent an application itself, its provided information will be employed by (future) ADAS applications. For this purpose, an environment model, capable of tracking and maintaining objects perceived by both local and remote perception sensors, has to be developed. Furthermore, this environment model has to provide an interface for queries, in order to extract information about specific objects. The vehicle-oriented part of the thesis addresses the following research questions:

What information about objects perceived by other ITS-Ss need to be shared to be considered by the receiving vehicle's ADAS applications?

- Objects enlisted in an environment model may either originate from local sensor data or from remotely received data. However, the question of the required least amount of data about an object in order to enlist it within the model has to be answered. Several requirements have to be accounted for: The environment model itself needs to be based on a flexible architecture for fusing and predicting remotely received objects along with local sensor data. Additionally, existing prediction models may need to be adapted and have to account for communication delays and much lower update frequencies compared to vehicle mounted sensors.
- For transporting the identified information from one vehicle to another, a specific message format is required. The message definition has to comply with existing ETSI conventions and standards. Therefore, it is important to provide a generic abstract format [246]. Additionally, most variables of the new message format should be taken from the ETSI ITS CDD to assist prospective standardisation efforts. Consequently, this thesis takes these requirements into account and develops a message format for realising *Collective Perception*.
- **Publications:** The work presented in [107] identifies variables for a prospective message format for the concept of *Collective Perception*.

What architectural requirements result from a real-time enabled environment model integrating *Collective Perception* in a vehicle?

- As described in section 2.2, an environment model provides a representation of the current driving environment of a vehicle. Objects within this representation can be added, whenever a perception sensor detects a new object. It is the task of the environment model to maintain spatial and temporal alignment of all objects tracked by the model. In case an object is perceived by several sensors of a vehicle, new measurement data has to be assigned, i.e. fused with the data of the same object within the database. Whenever an object is not perceived any more, it has to be removed from the database after a grace period.
- Additionally, object information received by V2X communication has to be added to the fusion process as well. Whereas the data of local perception sensors is refreshed frequently, V2X messages are not received deterministically, as their dissemination depends on the current channel load and dynamic state of the transmitter. Chapter 7 presents and implements an architecture for an environment model, focusing on the incorporation of V2X messages, especially in the context of *Collective Perception* in a real-time environment. The implementation focuses on both: on the possibility to query the environment model for those objects only perceived by local perception sensors as well as on the option to maintain objects received by V2X messages. Whereas the former is required to extract the data to be transmitted by the *Collective*

Perception message presented in chapter 5, the latter enables the comprehensive integration of objects solely received by means of V2X communication.

- **Publications:** A high-level object fusion architecture is presented in [107]. An architecture for combining the simulation environment outlined in section 3.1 with the real-time environment model developed as part of the *Microscopic Analyses* is presented in [94]. This combination is used for the sensitivity analysis regarding the error propagation inherent to *Collective Perception*.

How can ADAS applications profit from the realisation of *Collective Perception* and what are its limitations?

- When integrating remote sensor data in the environment model of a vehicle, a further challenge is the data accuracy required for fusing remotely received sensor data with local sensor information. The determination of the relative position between an object perceived by another vehicle and the receiving vehicle is based on two separate measurements: on the measurement of the local sensor mounted to the transmitting vehicle, as well as on the the measured Global Navigation Satellite System (GNSS) position of both the transmitting and the receiving vehicle. Consequently, an error propagation model for measurement inaccuracies, estimating the combined error when considering remote data in a vehicle's environment model has to be developed. Depending on the ADAS application, different requirements regarding the accuracy level of received sensor data exist: intervening applications require accurate object descriptions at least within the level of half a lane width, whilst applications merely issuing warnings may cope with more inaccurate object states. Section 7.2 presents an error propagation model in the context of *Collective Perception* and also discusses data quality issues.

- As a proof of concept, *Collective Perception* is validated in two automated vehicles driving on a race-track. The vehicles utilise the developed message format for continuously exchanging their locally perceived objects. Whenever an obstacle is perceived on the track by one of these vehicles, an avoidance trajectory is generated. *Collective Perception* provides a substantial benefit for the vehicle receiving the sensor data from the other vehicle: multiple runs on the track prove the effectiveness of *Collective Perception* for a collision avoidance scenario.

- **Publications:** In addition to the message format, the empirical results for the collision avoidance application are also presented as part of [107].

4 Related Work and Definitions

The idea of sharing sensor data with other agents has been a topic of research for quite some time. Hence, the current developments from related areas need to be considered, when developing a holistic concept for *Collective Perception* within the context of IVC. Section 4.1 presents the relevant work in this context, aggregated from different areas of research. For this purpose, a Systematic Literature Review (SLR) has been conducted in order to gain knowledge about the related work. The presentation of the SLR serves as a basis for several conclusions which are considered for the development of *Collective Perception* presented in the subsequent chapters. Afterwards, section 4.2 takes the review as a basis for providing several definitions of key terms used within this thesis.

4.1. Relevant Literature

The following survey is based on a comprehensive SLR and follows the approach presented by Okoli et al. [166]. A SLR is a multi-step process: the first step includes the presentation of the purpose of the review along with an explorative search. The second step defines relevant keywords which are combined to generate search expressions. These are used consecutively to search for relevant literature in databases related to the area of research. The extracted literature needs to be screened and appraised for its relevance. Eventually, the presented review has to provide a synthesis displaying the relevant conclusions for the further work [166].

4.1.1. Methodology

The purpose of the SLR is to provide a thorough, reproducible methodology for gaining an overview of the current state-of-the-art for sharing sensor data in the context of VANETs. It is not intended to provide a comprehensive overview of the development of IVC. Instead, the findings of the review serve as a basis for the development of the concept of *Collective Perception* and therefore as the starting point for the subsequent tasks, such as the definition of a common message format. As the general idea of exchanging sensor information in a network is not limited to research in the automotive field, the SLR also includes a brief overview of different, yet related fields of research.

The employed methodology is based on several iteratively developed search expressions regarding the broader research topic of *Collective Perception*. As the underlying idea of exchanging sensor information in a network is not limited to the automotive field, several synonyms can be found in literature to convey the same meaning. Therefore, the established search expressions consist of synonyms to cover a wide range of research areas. Maintaining the order of the groups, the search expressions result from all permutations of the groups displayed in Table 4.1. The asterisk resembles a wildcard. Four groups of relevant keywords

Table 4.1.: Extracted keywords for the Systematic Literature Review

(A	$\wedge$	B	$\wedge$	C)	$\neg$	D
collect*		perception		information		power
cooperat*		sensor		message		energy
collaborat*		vision		data		management
shar*				awareness		medic*

have been identified. Group *A* represents a collection of synonyms describing the broader topic of cooperation and sharing between agents. Group *B* outlines the purpose of the cooperation, i.e. the perception of the environment by using sensors or other systems. Without being specific, group *C* highlights that the sensor data has to be conveyed by some sort of data encapsulation technique. Group *D* contains keywords which have been excluded from the search after identification during the initial explorative search. These expressions have been employed to query the digital research libraries of the IEEE and the Association for Computing Machinery (ACM) and Google Scholar. The keywords of each group have been combined with logical operators in a metadata search. The keywords within each group are connected by *OR* ($\vee$) operators to form the search string in the form $(A \wedge B \wedge C) \neg D$. The identified literature has been filtered by relevant conferences and journal contributions. Additional tertiary sources have been added as well. As a next step, the literature has been grouped according to research areas. The following sections display the findings from these areas to confine the meaning of the term *Collective Perception* that will be used within this thesis. Section 4.1.6 summarises the findings of the survey and provides indications to be considered for the consecutive development of the idea of *Collective Perception*.

4.1.2. Wireless Sensor Networks

The research area of Wireless Sensor Networks (WSNs) introduces the basic concept of sharing sensor information. Usually, every node within the network is equipped with a certain set of sensors for applications such as tracking of objects or monitoring of the environment [154, 250]. Due to the large field of applications, the requirements for WSNs range from energy-efficient network nodes [8] to self-organizing routing algorithms [38]. The idea of using the sensor nodes within a network not only for their dedicated application, but for multiple applications in parallel, has been introduced in [30, 141]. The authors resume the idea of *smart dust*, which refers to the presence of a diverse set of sensors in different devices within a network. Although the sensors in each device serve a dedicated (primary) application, the sensor information within the network can be combined for deriving a profound understanding of the scenario and to reduce uncertainties. Therefore, sensors within a network can be treated as a common infrastructure and thus as a shared resource which needs to be managed. Chaczko et al. present a new paradigm, called *opportunistic information fusion*, envisioning the extraction of information required by an application different from the primary one. The sensor data required for the secondary application is gathered from different sensors within the network. In order to make use of any sensor within a network, the authors employ the IEEE P1451 standard which, amongst others, allows for a standardised self-announcement of the sensor within a network [30].

Besides employing connected sensors for multiple applications simultaneously, they can also be used in conjunction with GNSSs to improve the localisation capabilities of a network node. Buchli et al. present an approach for dramatically reducing the localisation error by equipping several sensor nodes with GNSS receivers [22]. The nodes forward their GNSS raw-data to a dedicated base-station which performs data post-processing by a remote application. Although the information from several nodes is required to perform data processing and to increase the localisation quality, the network nodes do not exchange information with each other but with a central base-station.

Xiao et al. provide a simulation study to show that the information quality for target tracking can be improved by adaptive sensor scheduling [247]. The authors show that the detection probability of a particle moving within a region covered by several sensors can be increased. The measurements of each sensor are combined by using an extended Kalman filter based on a constant velocity model. Additionally, cooperative sensing improves the tracking accuracy due to a larger number of available measurements.

Collaborating sensors as part of WSNs may also be used to increase the sensing region of a system equipped with sensors, e.g. for monitoring purposes. Several independent network nodes are scattered within a certain area for different monitoring purposes. Kulau et al. placed several small sensor nodes on a potato field to monitor parameters such as temperature and soil humidity. The working environment of these nodes, however, brings along several challenges. As cables between nodes, i.e. for providing power are not feasible on a potato field, the nodes have to be equipped with batteries. This, in turn, requires low energy consumption of the nodes to ensure persistent operation [138].

A different detection and monitoring application is presented by Merino et al. The authors propose a cooperative perception system for detecting forest fires with the help of several Unmanned Aerial Vehicles (UAVs). The employed vehicles are equipped with different sensor modules for the purpose of cooperatively locating forest fires. Upon detection of a potential fire, the UAVs approach from different directions for estimating its spread. By sharing sensor data between the vehicles, the data to be transmitted to a base-station can be reduced as some of the required computation can be performed by the node itself. Furthermore, due to the heterogeneous sensor setup, false alarms can be reduced [154, 155].

Cars can also be seen as a sensor node as part of a WSN. Xiaoxiao et al. point out that although a car is equipped with a multitude of sensors and is generally not constrained to energy shortage, the sensor mobility presents a challenge regarding the communication effort. The authors present a simulation study which uses the vehicle's sensors to monitor environmental information such as temperature, air pollution and traffic noise [248]. For monitoring purposes, the mobility of the sensors presents a challenge as the measurement data has to be transferred to a central instance frequently. To reduce communication requirements, a compression mechanism is used to aggregate data collected by the distributed network nodes.

4.1.3. Robotics

In the context of robotics, Schmickl et al. present a first definition of the term *Collective Perception* as ‘a way that allows taking advantage at the global (swarm) level from a mass of complex data sensed in parallel on the individual level’ [193]. In their proposal, the behaviour shown by honeybees is applied to miniature robots to find a common goal within a defined region. According to the authors, honeybees make use of mouth-to-mouth contacts to control the collection of preferred pollen over nectar. The robots used for their study can move within a predefined region and, like the honeybees, aim at reaching a common target. The robots are limited in their sensing and communication range via infrared-diodes. Upon reaching another robot’s communication range, *virtual nectar* is exchanged according to a dynamic transfer-rate. The amount of transferred nectar determines the direction of a robot’s movement. This leads to an intrinsic behaviour which causes the robots to move along the gradient of *virtual nectar* towards the source. Hence, the only information exchanged between the communication partners is a certain amount of *virtual nectar* [193].

A different bionic approach is presented in a simulation study by Arena et al. In close resemblance to ants, the simulated agents aim at arriving at a common target, whereas the agents are only allowed to communicate, whenever either the target has been reached (to adapt the behaviour of other agents) or deadlocks have occurred. The exchanged data includes the last steps performed by the agent in order to reach the target [10].

Similar, albeit more complex approaches can be followed to enhance a robot’s location estimation. The work presented in [127, 152, 167] propose the combination of several sensors mounted to moving robots and standstill objects for recognising landmarks which can be used for estimating a robot’s position. The sensors on the moving robots are also used to generate an occupancy grid of the current environment which may be shared among other robots, e.g. for path planning purposes in a local environment. Rather than using a GNSS, landmarks are used to generate a relative position from one robot to another, therefore rendering applications without satellite coverage possible.

In case of moving obstacles, Shah et al. propose a cooperative perception mechanism between several UAVs to calculate collision free trajectories. The method incorporates different perception angles of the same obstacle from different UAVs to predict the movement of the obstacle [197]. The mechanism for exchanging the data, however, is not presented. Instead, the required data fusion mechanisms to combine data from several sensor sources is introduced. In a similar fashion, the authors of [103, 220] propose a target tracking application for mobile robots. For this purpose, the robots share their local sensor data with each other to track a moving obstacle within their sensor range. Again, whilst the authors are very specific regarding the fusion algorithms that may be used for continuous tracking, an analysis regarding the required information and communication capabilities is not presented [220].

The work presented by Spaan et al. highlights the benefits of shared sensor data within the vehicular context. Here, several moving robots perform a path planning task in an uncertain environment which is perceived by their on-board sensors. The authors introduce cooperative perception in order to reduce the uncertainty by sharing sensor data between the robots [208]. Imperfections in the sensation of the robot's environment are modelled by means of a *Partially Observable Markov Decision Process*. The results show that by sharing state variables about the environment, object detection and classification can be improved significantly. However, the work neither reveals the actual content of the data packets, nor does it present the resulting impact of the data exchange on the inter-vehicle network.

4.1.4. Defence

The idea of cooperating sensors on a larger scale is also researched within the defence industry. Aboutalib proposes a *cooperative fusion architecture* which enables the collaborative identification of combat targets by using several nodes such as UAVs equipped with similar sensors. In contrast to the approaches presented above, every network node is able to pull information from the others, rather than push updated information into the network on a regular basis [3]. Besides reducing the network traffic, as information is only transmitted when required by a node, each node can decide whenever it requires updated information. However, this approach requires a powerful fusion algorithm running on each node, which is capable of processing local and remote sensor data in real-time. To reduce the amount of information sent over the network, each transmitting node applies a relevancy check of the data to be transmitted. Additionally, the information gathered from the UAVs is also used for improving localisation in regions of weak GNSS coverage. Even in areas with denied GNSS-coverage, localisation of nodes can be realised by means of fusing data collected by several high-precision sensors such as inertial measurement units, infrared horizon scanners and electro-optical sensors [3]. The key concept to take away here is the idea of requesting sensor data from other agents rather than continuously exchanging data. However, a dedicated message describing the data to be transmitted, is not presented.

The work presented by Yan et al. couples several UAVs with the purpose of cooperatively searching and destroying a target. Rather than a single UAV making the decision to confirm and attack a target, several vehicles combine their information base for this purpose. The authors highlight that for reasons of security and practicability, there is no central instance coordinating the actions of the vehicles [249]. Instead, a decentralised algorithm decides when to share which information with other agents. The system is limited to a preknown mission environment which is split up into a grid which may be occupied by the questionable target. Although the authors assume a noise free and instantaneous network, its communication range is somewhat limited. Within the communication range, an information-sharing policy specifies three types of triggers for sharing information. Regular broadcasts are used as beacons to exchange the current sensor readings for the current cell. Event-triggered broadcasts are used upon the occurrence of a special event, such as an attack command. Whenever UAVs are close to each other, the opportunistic exchange principle triggers the exchange of the complete local database [249]. The proposed concept provides an overview of the different occasions of when to share sensor data under which circumstances.

4.1.5. Automotive

Most of the identified literature can be assigned to the automotive context which is grouped into the following categories.

Alternative Concepts of Collective Perception Within the automotive research, different associations related to the term *Collective Perception* exist. Bensrhair et al. describe *cooperative vision* as the combination of two different sensors, a mono- and a stereo-camera [14]. Within this thesis, however, the term *Cooperative* or *Collective Perception* always includes a communication component, i.e. the active exchange of data between at least two agents.

Wallart et al. present a different approach for the exchange of sensor information: rather than using vehicle-mounted sensors, fixed distributed sensors along a highway cooperate to create a global interpretation of a scene [231]. Due to the immobility of the sensors, several blind areas exist that cannot be observed. For tracking objects moving within the scenario, sensors create a so-called *Domain of Occurrence Probability* which describes the appearance probability of a detected object within the range of any other neighbouring sensor. This probability is sent to other sensor nodes, thereby enabling tracking of objects within a large area [231]. The idea of *cooperative distributed vision* is suitable for scenarios such as highway traffic monitoring and the tracking of vehicles within a defined region. The vehicles within the network, however, do not actively participate in the communication.

Yet another approach is presented by Reiss et al. The authors introduce the term *Collaborative Situation Awareness* and interpret a vehicle as a mobile sensor node being part of a larger WSN [182]. Rather than exchanging information about other traffic participants perceived in the vehicle's vicinity, the on-board temperature, precipitation and acceleration sensors are used to detect adverse weather conditions. The locally collected environment conditions are then transmitted to other vehicles, which have to perform a spatio-temporal alignment of the received data for their own fusion process. Upon approaching an area of increased risk of aqua-planing, for example, the driver can be informed accordingly. Whereas this application could have also been realised by exchanging DENMs, as introduced in subsection 2.2.1, the authors propose exchanging a vehicle's internal belief about the existence probability of an event. This belief is not only based on the data of internal vehicle sensors but also includes the data of other vehicles within the communication range [182].

Getting closer to the notion of *Collective Perception* as presented in section 1.1, Hao et al. present a so-called *see-through* application. Rather than exchanging abstract descriptions of a vehicle's environment, the authors present a methodology for merging another vehicle's camera images into a receiving vehicle's reference frame. Overlaying these images generates an augmented reality image of the current driving situation, in which the other vehicle's image is used to reveal the traffic situation behind occluded areas from the driver's perspective [110]. Although focusing on solutions for communicating these images between vehicles, a similar idea is presented in [6]. This application may be used as an input for feature extraction algorithms as part of an image recognition facility within a vehicle. The extracted data may then be received by an environment model which is the basis for any ADAS application.

Improving Vehicle Localisation As outlined in subsection 4.1.2, a combination of local perception sensors and IVC can be used for improving the localisation of a vehicle. The research presented by Challita et al. shows how GNSS outages can be compensated, when using local sensor data for the localisation as well. For this purpose, all vehicles need to be equipped with V2X communication to exchange their current position. The authors introduce a fusion algorithm for matching the self-announced position of other vehicles with the local sensor data [31]. Upon disrupted GNSS measurements, this matching is used for estimating the vehicle's own position based on the relative distance to another detected vehicle and its corresponding received global position.

A different approach for improving the position estimation is presented by Ponte Müller et al. The authors discuss whether differentiation of GNSS pseudo-ranges yields better results for relative positioning compared to the consideration of absolute positions exchanged between vehicles, as provided by the CAM [173]. Their work is extended in [174], where the term *Cooperative Positioning* is introduced. The contribution combines local sensor data with data received by CAMs to improve the estimation of the relative distance to perceived objects in situations of obstructed sensor visibility. The authors also include a presentation of the performance of their employed communication system to highlight the capabilities of exchanging position data, especially in situations of obstructed LoS scenarios [174].

Franke et al. present a similar approach, where local sensor data is fused with data received by CAMs. However, rather than improving the estimation of the relative position, remotely received CAM data is used as a complementary data source under LoS conditions for local sensor data to speed up the plausibility check of safety functions [96].

Infrastructure Facilities A different approach to shared sensor data is proposed by several publications integrating infrastructure facilities into the communication network as well. Fanyu et al. present an architecture, in which sensors on vehicles cyclically offload their local sensor data to RSUs. Additionally, static road sensors also measure the current traffic flow and store the data received from passing vehicles. The proposed mechanism combines both sensor data to provide data for an enhanced route guidance application to reduce traffic jams [91]. The proposed protocol for exchanging sensor data, however, does not comply with the ITS G5 standard, as group formations and special query-response mechanisms have to be followed.

Another approach incorporating RSUs is called *Cooperative Vehicular Information Collection* [118]. Here, a central smart infrastructure facility monitors an intersection and manages coordination amongst approaching vehicles. The authors argue that continuously exchanging vehicle positions and sensor data causes severe channel congestions. However, as a fixed RSU is able to provide accurate information about object positions within the intersection, problems connected to GNSS inaccuracies can be avoided. The presented approach aims at exchanging an occupancy grid of the intersection opposed to object descriptions which may be used by ADASs [118].

Hence, RSUs in the context of *Collective Perception* as envisioned in section 1.1 may be suited for data offloading to central back-ends, temporal data storage or, in combination with stationary sensors, serve as a secondary data source for abstract object definitions.

Sensor Data Fusion and Map Merging When combining remote sensor data with locally perceived data, a methodology for fusing both sources has to be employed. The combination of data gathered from several sensors mounted to the same vehicle already brings along challenges which are subject of several publications [4, 160, 238]. For this constellation, sensor measurements occur at a fixed frequency and the relative position of the sensors do not change. The result of any fusion process is usually an object list, providing an abstract description of perceived objects (e.g. other vehicles, pedestrians, buildings, etc.) within the vehicle's reference frame. The facility for fusing the sensor data from different sources and for providing the aforementioned object list is referred to as an *environment model*. Wender et al. present a high-level fusion architecture which explicitly incorporates remotely received data, e.g. via V2X communication [239]. A special instance responsible for preprocessing, tracking and classifying objects exists for local sensor data. The architecture treats V2X communication as a separate dedicated sensor. Hence, a similar instance as the one for local sensors exists for received V2X messages, being responsible for temporal alignment of the received data. The inaccuracy caused by positioning systems of a GNSS leads to a localisation error that needs to be accounted for in association algorithms, when combining local sensor data with position information received from other vehicles. The authors propose a method of calculating the association probability of data perceived by local sensors and received data. All sensor data is then processed by an association facility which performs the actual data fusion process. The authors highlight that in most scenarios, a purely distance-based association of local sensor data with V2X data will fail, due to GNSS inaccuracies [239]. However, as the sending vehicle is able to deliver a very accurate description of its own dynamic state and geometric extent, additional variables can be used for the association process. This problem is also known as *Car-Matching* and has been addressed by [96].

Wei et al. propose a similar approach but extend the capabilities of the environment model beyond the mere provision of a fused object list. Additionally, the model is also responsible for matching the maintained objects on a map and for predicting the movement of these objects. A risk-assessment function also includes an evaluation of each predicted object movement with respect to the host-vehicle [235].

A first hint at information that needs to be included in a prospective message format for *Collective Perception* is given by Zoghby et al. The authors present an algorithm which creates a dynamic map representing the current driving environment of a vehicle. Other vehicles are enabled to exchange information about their locally perceived objects with each other by means of IVC. Rather than defining a message format, the authors state that for the fusion algorithm to work, at least the relative distance to the sender, the velocity, the object age and its classification need to be provided. The distance and velocity components need to be accompanied by covariance matrices to provide accuracy estimates [254].

Woo et al. showcase a holistic approach for exchanging information of vehicle mounted Lidar-sensors. Next to the aforementioned problem of map-merging, i.e. the localisation of a vehicle and its perceived objects on a pre-known map, the problem of fusing information about the same objects collected by local sensors and received from another vehicle is addressed [244]. The introduced fusion algorithm uses the perceived speed of an object as the common information in order to derive association hypotheses. In the described set-up, an autonomous vehicle follows two manned vehicles. The manned vehicle in the middle transmits its sensor information to the leading manned vehicle, which merges this information with its locally perceived objects. The first manned vehicle, in turn, transmits the merged information to the autonomous vehicle at the end of the queue, which uses a path planning algorithm to determine its next waypoint. The authors also analyse the impact of the employed communication solution on the performance of the system. Depending on the size of the message — and therefore the amount of data transmitted (e.g. raw Lidar data or already processed data) — substantial communication delays of up to 8 s were be observed. The information about the communication delay is used to determine a coordinate offset for the path-planning algorithm [244]. In their further work, Liu et al. analyse how so-called *Cooperative Perception* can be employed to improve motion planning algorithms. Exchanging sensor information between the vehicles increases both the visibility beyond the LoS as well as beyond the FoV. This enables path finding algorithms to reduce uncertainty for paths and thus the costs associated to these paths. Additionally, long-term perspective planning can be realised due to the increased range of visibility [145]. Although the findings indicate a significant increase in the FoV, the average utilised messages were 'usually' below 5000 Bytes which is well above the acceptable message sizes in the context of ETSI ITS G5 communication.

Holistic concepts for shared sensor data within IVC As part of the research initiative Ko-FAS [1], the realisation of cooperative sensors for *Collective Perception* has been addressed. Within the initiative, three working groups focussed on the topics of cooperative sensors (Ko-TAG), cooperative perception (Ko-PER) as well as cooperative components (Ko-KOMP) in a vehicular environment [252].

The project has been among the first to develop a holistic concept for sharing sensor data between vehicles within an ETSI ITS G5 framework. Based on the ITS G5 inspired sim^{TD} communication stack [12], Rauch et al. analyse the performance of a fusion architecture for local and remote sensor data [178]. As part of the project, a proprietary Ko-PER message, the so-called Cooperative Perception Message (CPM) [171], has been developed. The message is used to share information about locally perceived objects with other vehicles in communication range. However, the message includes many variables which are included

1 `http://ko-fas.de/` (Accessed: 11/13/2016)

for research purposes only, thus increasing the resulting message size unnecessarily[1]. The authors conducted several experiments to determine the transmission latencies that can be observed for traditional CAMs and CPMs. As part of these experiments, the number of participants as well as the sending rate have been varied to find that the channel load and message error rates increase significantly with both size and transmission frequency of any message [178].

Next to the message definition, the project also proposed a high-level sensor data fusion architecture, specifically incorporating remote sensor data. The proposed fusion architecture consists of five core elements [179]. The first three components keep track of locally and remotely perceived objects and are also responsible for sending and receiving the aforementioned specific messages such as the CAM or the CPM. A temporal alignment facility is responsible for the prediction of every perceived object to the current time, using a suitable motion model. A second spatial alignment facility employs an *Unscented Kalman Filter* to combine measurements from different sources. The separate lists of locally and remotely perceived objects are fused in a so-called *global fusion* component which can be accessed by any driver assistance system. Three different approaches for realising a global fusion module are detailed in [180]. The underlying idea of any of these approaches is to match multiple sets of discrete points resulting from different sensor measurements, where at least one point belongs to a perceived object. Eventually, an iterative deterministic algorithm presented in [15] is found to show the best performance [180].

The participants of the project even demonstrated the usability of *Collective Perception* as part of an advisory warning application for an intersection. Seeliger et al. describe a scenario in which several vehicles exchange CPMs to generate a holistic knowledge of all traffic participants approaching the intersection. Besides other vehicles sending their local data, the intersection has been equipped with several sensors. Hence, a RSU is also able to provide observations about objects passing the intersection. The authors demonstrate that due to shared sensor data, severe traffic conflicts due to obstructed LoSs could be avoided altogether [196].

A comparable approach has been followed by Tischler et al. Similar to the Ko-FAS project, the authors propose two components which should be part of any message for *Collective Perception*: a description of the dynamics and the pose of the sending vehicle, as well as a dynamic container including the perceived objects of the sender [218]. The first information is required to perform the corresponding coordinate transformations to the receiver's reference frame. The second information then conveys the properties of the detected objects. The level of detail with which objects can be described depends on the employed local sensors. The authors do not present a message format but focus on various aspects of the prediction and data fusion processes [218]. However, their related work indicates that an optimised image compression mechanism shall be applied to video data

1 The maximum size of the CPM is 1343 Bytes [178]

prior to transmission [219]. It is up to the environment model of each vehicle to extract features accordingly.

The more recent European *AutoNet 2030* project focuses on researching technologies and algorithms for cooperative systems [39]. One of these technologies is called *cooperative sensing* and also aims at exchanging sensor data between communicating vehicles, just like the Ko-FAS project [115]. For this purpose, two mechanisms are introduced: the first mechanism includes a data field for the distance to the preceding vehicle as part of the CAM to be used by a cooperative ACC application. Due to changes of the abstract syntax of the legacy CAM, backward compatibility is no longer provided. In combination with on-board sensors, data verification and validation of CAMs is proposed by [165]. The second mechanism is a novel message format called *Cooperative Sensing Message (CSM)*. This message, as opposed to the CPM proposed by the Ko-FAS project, provides an abstract description about information of up to 16 detected moving objects [114]. The message is generated at a fixed rate of 1 Hz and is disseminated on the ITS G5-SCH 1 to be able to deal with the expected higher data loads, especially since multiple other messages are to be sent on the ITS G5-CCH as part of the project as well [115]. Although considered in the design of the message and the selection of the communication channel, a dedicated analysis of the network limitations is not presented. Furthermore, the age of the detected objects cannot be determined, as only a single global timestamp for the message is provided. As a consequence, the state variables describing the objects included in the message need to be predicted to the dissemination timestamp. The prediction mechanism, however, is not specified. Another drawback of the presented approach is a missing description of the disseminating ITS-S's sensory capabilities, i.e. to derive the current overall FoV.

Vasic et al. propose a somewhat different approach, called *Cooperative Perception*: In addition to sharing dynamic state variables, vehicles exchange *Probability Hypothesis Density* intensities for detected objects. The findings show that the tracking quality of objects can be increased, especially when the same object is observed by several vehicles from different perspectives [224]. The concept comes short of a description of a common data format for objects to be transmitted. This approach dictates to use Gaussian Mixtures as part of the fusion algorithm. In [225], the same authors present an overtaking application based on their proposed concept of *Cooperative Perception*.

4.1.6. Findings

The SLR presents a thorough analysis of related literature for the idea of exchanging sensor data between several agents. Multiple disciplines have been identified to employ similar concepts, albeit a common definition for shared sensor data does not exist. Figure 4.1 summarises the identified research topics and key concepts. From here, several conclusions can be drawn, which serve as valuable input for the development of a holistic concept for *Collective Perception*. Although anticipating results, references related to findings presented in this thesis are provided, whenever applicable:

Figure 4.1.: Identified key-concepts for *Collective Perception* by the SLR

The term *Collective Perception* No common definition for shared sensor data, especially in the automotive context seems to exist. However, the most common terms *Cooperative Perception*, *Collaborative* or *Cooperative Sensors*, *Cooperative Vision*, *Collaborative Situation Awareness* and alike are always employed for the same purpose: sharing sensor data between agents for different applications. Therefore, section 4.2 derives a definition for the term *Collective Perception* used within this thesis. Furthermore, it is apparent that all authors agree on the usefulness of sharing sensor data. The potential of shared data within a network, however, greatly depends on the number of communication partners. The required number of communication partners capable of *Collective Perception* — the *critical mass* — for the applications to be effective, however, is not presented. Consequently, section 6.5 provides an analysis regarding the necessary market penetration rate of V2X communication for *Collective Perception* to be effective.

Data Transport Most of the identified literature does not state an explicit mechanism for exchanging sensor data. Only the work within the automotive context proposes several different message formats for transporting the required data. However, none of these messages are optimised for either the resulting message size, nor do the corresponding authors focus on the compatibility with the existing US or European standards. Although some authors provide insight to the performance of their proposed message formats, their proposals are not picked up by their further work. The CPM format proposed by the Ko-FAS project focuses on research purposes and includes many irrelevant data fields. Similarly, although exhibiting a much smaller footprint compared to the CPM, the CSM message proposed by the AutoNet 2030 project is not investigated further. Instead, the idea of shared sensor data is distributed to different message formats, such as their modified version of the CAM. Therefore, the existing literature does not propose a viable message format which conforms to any existing standards for the purpose of exchanging sensor data within the context of IVC. Section 5.2 therefore addresses these shortcomings and proposes the required data containers and message formats for *Collective Perception*.

Purpose Future ADAS applications require a comprehensive understanding of the current driving environment of the vehicle, especially in the context of SDSs. Irrespective of the underlying communication technology, the identified literature sees V2X communication as the key concept for extending the horizon of perception of vehicles. An extended awareness of the vehicle's environment beyond the LoS of its sensors not only allows for a considerable improvement of already existing ADASs, but also for the development of novel systems in the domain of both comfort and safety systems. Therefore, the exchange of environment information between vehicles and other traffic participants can be seen as an enabler for these systems. The concept can also be used to improve the relative localisation of vehicles, by considering landmarks detected by local sensors. Different effects associated to *Collective Perception* are identified in subsection 6.5.2. A validation of *Collective Perception* in a real-world obstacle avoidance scenario is presented in section 7.3.

Environment Model All sensor data needs to be maintained by a central component which generates and maintains a database depicting the current driving environment of a vehicle. This component is generally called the *environment model*. Instead of ADAS applications gathering the required sensor data, the environment model is responsible for extracting objects from all available sensor sources. Whenever applicable, the data from several sensors should be combined, to provide a more detailed description of the driving environment. Although the related work highlights the necessity of such a model, the architecture and applicability differs with respect to the application. Section 6.3 introduces the concept of an environment model as part of a macroscopic simulation framework. In section 7.1, a dedicated architecture for an actual vehicle implementation is presented.

Data Fusion Irrespective of the field of application, solving the problem of fusing local and remote sensor data is key to enabling *Collective Perception*. Depending on the application as well as on the employed communication solution, different fusion algorithms have to be applied within the environment model. The main issues of the data fusion process result from the need of temporal and spatial alignment of the input data. Whereas temporal alignment requires the use of adequate motion prediction models, spatial alignment requires non-linear transformations of the data to transform the received object information into a common reference system. Furthermore, different levels of data fusion processes have been identified: whilst some approaches merely focus on the provision of an object list, others also perform matching of objects on lanes of high-fidelity maps. The SLR revealed that data fusion from different sensors is a key topic, although multiple approaches exist. Along with the approach changes the data that needs to be provided for the fusion algorithm to work. Whilst some algorithms require the raw sensor data, i.e. compressed images for feature extraction, others rely on abstract object description where the sending node has to select features of the objects to be included. For the identification of the limitations of data fusion processes and of prospective data quality requirements, section 7.2 develops an error propagation model for estimating the accuracy of remotely received objects.

Network Limitations Contrary to vehicle mounted sensors, which information is readily available for data processing in ECUs via the vehicle internal bus systems, remotely received sensor data is subjected to communication effects which have to be accounted for. Apart from the delays introduced by the propagation characteristics of electromagnetic waves, the employed communication solution adds substantial delays due to channel-access mechanisms as well as due to delays inherent to the employed communication stack, e.g. due to DCC operations. Another challenge results from the need of interoperability. Especially in the context of the automotive industry, where ITS-Ss from several manufacturers have to communicate with each other, the definition of a common *language* is required. For this purpose, the C2C-CC, ETSI and other institutions undertake substantial standardisation efforts to enable interoperability between the different ITS-Ss. In turn, the working principle of *Collective Perception* will have to be standardised as well. Hence, any message to be developed should closely follow existing standards and protocols. The SLR shows that the definition of a common message format has not been the focus of the related work. Instead, mainly proprietary solutions were presented. Therefore, section 5.3 proposes different message formats for realising *Collective Perception*, complying with existing ETSI standards. An analysis regarding the limitations resulting from the employed communication technology is presented in section 6.6.

Security Although not explicitly analysed as part of the SLR, some of the authors mention the issue of data security and privacy aspects. Irrespective of the communication technology employed for V2X communication, the development should aim at respecting the privacy of all traffic participants. Additionally, exchanging information about the perceived objects has to concur with the security mechanisms proposed by the V2X standardisation authorities. Furthermore, long-distance tracking of objects within the network has to be prevented for privacy reasons [119, 181].

These findings serve as the foundation of the subsequent analyses. Chapter 5 takes the existing approaches of the *Ko-FAS* and *AutoNet 2030* projects as the starting point for the derivation of new message formats for realising *Collective Perception*, albeit taking existing standards into account. Chapter 6 addresses the missing aspects related to the data transport: several detailed simulation studies identify the required number of communication partners for the concept to be effective and analyse prospective limitations resulting from the communication stack. In chapter 7, the identified approaches concerning the implementation of the environment model are considered to derive an accuracy analysis relevant for the data fusion process.

4.2. Terms and Definitions

This section introduces definitions of several terms used within this thesis regarding the development of *Collective Perception*.

Objects As shown by the SLR, sensors can be used to perceive an agent's environment. As such, the raw data of the sensors is analysed to extract so-called *objects*. These can be interpreted as a set of all other traffic participants such as neighbouring vehicles, bikers, pedestrians and alike. Because of their ability to move within physical boundaries, they will be referred to as *dynamic objects*. Their counterpart, *static objects*, cannot move (e.g. trees, buildings, crash barriers and alike). Objects can be represented mathematically by a set of variables, describing, amongst others, their dynamic state and geometric dimension.

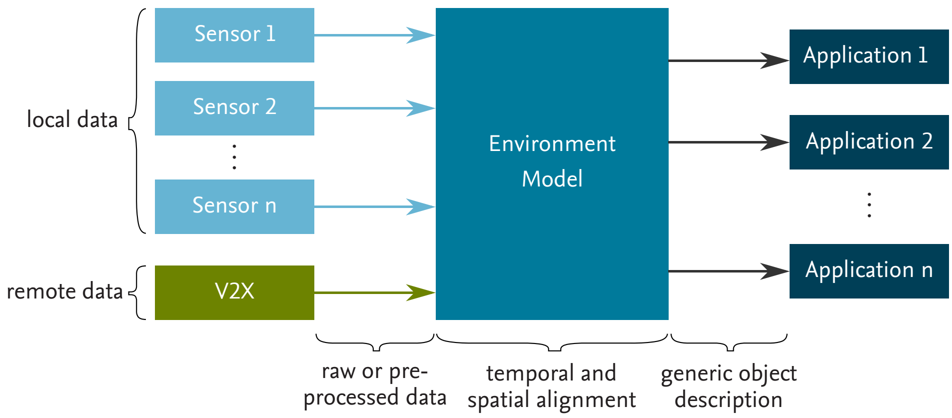


Figure 4.2.: Environmental model as a middleware between sensors and ADASs applications

Scene Information This information aims at providing a comprehensive description regarding the scenery surrounding a dynamic object and consists of attributes specific to elements of the scenery. This type of information may report the current status of traffic-lights, provide supplementary evidence for the current position of a vehicle (e.g. lane-number) or describe the validity of traffic regulations (e.g. road-signs).

Environment Model The ego-state of a vehicle can be described by a confined set of variables, which is often measured by vehicle mounted sensors. The environment of a vehicle, however, has to be perceived by a different set of local perception facilities, such as a Radar or Lidar sensor (see chapter 2.2.2). Depending on the metering principle, the sensors scan their environment to collect different data about objects in their vicinity. The sensor-raw data is pre-processed to remove noise and artefacts as well as to differentiate static from dynamic objects [209]. The detected objects are then reported to the environment model, which creates a spatial representation of all objects within the vehicle's vicinity. The model consists of a list of mathematical descriptions of static and dynamic objects currently known to the vehicle — irrespective of the sensor source. Additionally, the model maintains the temporal and spatial integrity of all objects by means of suitable prediction algorithms. As the same object could be detected by more than one sensor, the environment model is also responsible for merging redundant and for adding complementary data to an object already tracked by the model [41, 210]. Hence, an environment model can be interpreted as the middleware between the sensors and any ADAS application, as depicted in Figure 4.2. The sensors deliver their raw- or pre-processed data to the environment model, which keeps track of all objects that can be derived from the data. The model provides a generic description of these objects, irrespective of the data source. All objects currently processed within the environment model are called *maintained*.

Local vs. Remote Data Data gathered by means of sensors mounted to the vehicle is referred to as *local* sensor data. Any object information gathered by means of communication is referred to as *remote* data. Both sources may be combined as part of the data fusion processes of an environment model.

The term *Collective Perception* shall be used as a synonym for exchanging processed sensor data between vehicles in order to increase each other's FoV. In conjunction with the findings presented in section 4.1, the following definition is proposed:

Collective Perception. *The concept of actively exchanging locally perceived objects between different ITS-Ss by means of any V2X communication technology. The concept decreases the ambient uncertainty of ITS-Ss by contributing information to their mutual FoVs. At the core of the concept stands a common message format describing locally perceived objects and providing the information required by the receiver to perform data fusion processes.*

In combination with an environment model, the principle of *Collective Perception* provides the basis for future applications in the context of cooperative driving.

4.3. Summary

This chapter presents a thorough review of the relevant literature in the context of sharing sensor data between agents. The idea of sharing sensor data can be found in four different research areas: in the domain of wireless sensor networks, shared sensor data is often used for monitoring purposes, along with high requirements regarding low energy consumption and efficient communication schemes. In the context of robotics, the idea of *swarm data* is applied to path-finding and target tracking applications. In the domain of defence applications, shared sensor data is also used for improving localisation of mobile nodes, especially in scenarios of denied GNSS coverage. However, the area of automotive research provides most of the identified literature: several research projects introduced the concept of sharing sensor data between vehicles and other traffic participants and also implemented prototype ADAS applications relying on remote sensor data.

When combining the research from these disciplines, it is found that a common concept for sharing sensor data between agents in the automotive context does not exist. Therefore a first definition of *Collective Perception* is provided based on the literature review. Furthermore, the review identified missing elements that have not been addressed by others, such as the definition of a common message format for transporting detected object information or an analysis of the communication requirements. Instead, most of the related work focuses on data fusion algorithms for combining measurements of local sensors with remote sensor data.

5 Message Development

At the core of a concept for sharing sensor data between traffic participants stands a methodology for transporting this information. Simply exchanging an object list provided by an environment model is not preferable, as requirements from different perspectives, as detailed in chapter 4, have to be considered. This chapter first presents the relevant components of the ITS G5 framework and introduces several coordinate systems which need to be considered, when developing mechanisms for *Collective Perception*. Second, the variables which are required from the perspective of a data fusion process and which have been optimised to also meet the requirements of the network perspective are introduced. The third part of this chapter then introduces two methodologies for combining these variables to realise the concept of *Collective Perception*. Eventually, the fourth part covers principles to be considered, when generating messages in the context of *Collective Perception*.

Most of the work presented in this chapter is primarily based on the following publications: [104, 107].

5.1. Framework Requirements

Exchanging sensor information between ITS-Ss inevitably requires the definition of additional variables which may be accommodated either as part of a new message format, or as an extension to already existing ones. Within this thesis, the ETSI ITS G5 protocol stack has been selected as the communication technology to share sensor data between vehicles. Therefore, the general framework and existing ITS G5 standards and conventions have to be considered, when developing a new message format.

5.1.1. Communication Framework

As outlined in section 2.2, all messages defined as part of the ITS G5 standards employ a data serialisation technique based on the common OSI ASN.1 standard [246]. This notation enables an abstract description of data structures, without focusing on a special runtime environment. Instead, an abstract definition of the data to be transferred is described. Each target environment employs a corresponding encoder to generate the transfer syntax which is the actual byte stream to be exchanged. Hence, ASN.1 can be used for realising communication of complex data structures between heterogeneous systems [45]. The generated transfer syntax depends on the applied encoding rules. The first kind of encoding schemes available for ASN.1, the Basic Encoding Rules (BER), employ the common type-length-value encoding, which has its benefits in terms of being able to decode incomplete streams, albeit at the costs of a rather inefficient encoding scheme in terms of the resulting stream size. ITS G5 standards employ the UPER supported by ASN.1, which do not include type tags for the encoded data types. This requires knowledge about the abstract syntax definition on the decoding side which has been used for generating the transfer syntax [139]. However, backward compatibility and further extensions of the message content is still provided by means of ASN.1 extension markers '...' within the definition of the abstract syntax. To increase the efficiency of the transfer syntax, UPER disregard octet boundaries when packing the data structure into the byte stream to be transferred [45].

The ITS G5 standards provide a collection of ASN.1 definitions of certain variables as part of a Common Data Dictionary (CDD). The standard message formats found within the ITS G5 standards, such as the CAM or DENM, essentially represent a collection of these variables with some special addenda. Therefore, any new message format or data containers developed as part of the concept of *Collective Perception* should employ variables from the CDD [83], whenever applicable. Furthermore, the BTP shall be used for multiplexing the new message format to the corresponding services.

5.1.2. Coordinate Systems

As sharing of sensor data inevitably requires appropriate coordinate transformations, the relevant coordinate systems and reference frames need to be introduced first. Figure 5.1 depicts all coordinate systems that are relevant for this thesis.

WGS84 The World Geodetic System of 1984 (WGS84) introduces a coordinate system fixed at the earth's centre of mass. Additionally, a geocentric ellipsoid of revolution describes

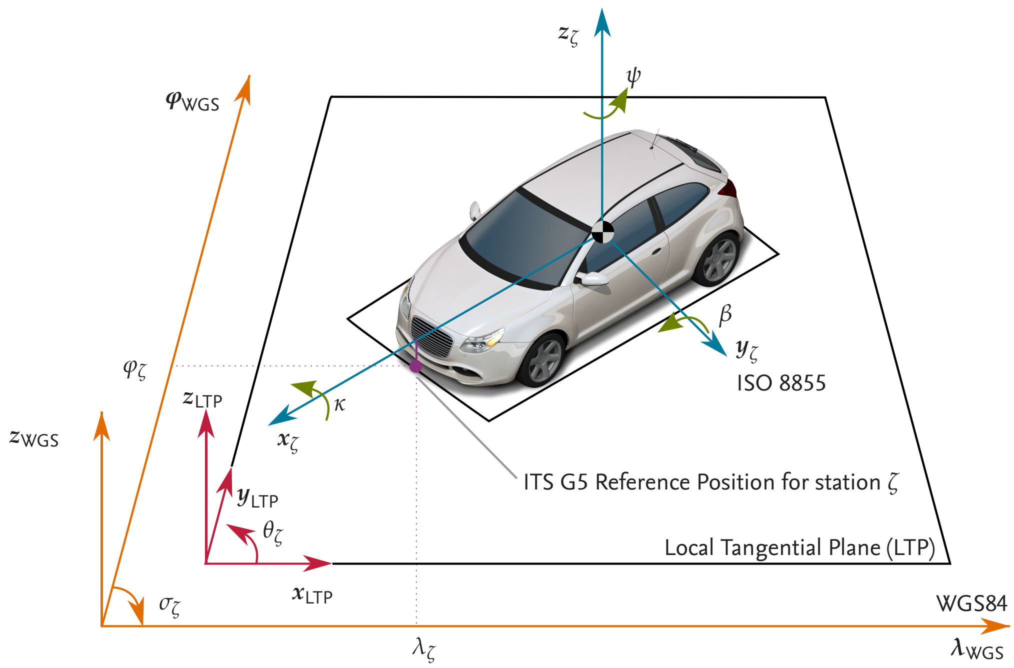


Figure 5.1.: Coordinate Systems

Table 5.1.: Specification of the WGS84 reference ellipsoid [163]

Semi-Major axis a	6 378 137.0 m
Reciprocal of Flattening $1/f$	298.257 223 563
Angular velocity of the Earth ω	$3\,986\,004.418 \times 10^8$ rad/s

the shape and hence the surface of the earth. This ellipsoid is defined by a semi-major axis a as well as by its flattening f, the relation between the semi-major and the corresponding semi-minor axis, as listed in Table 5.1. Furthermore, the ellipsoid serves as the reference surface which is used to describe a global position on the earth [163]. This is achieved by overlaying a network on the ellipsoid consisting of latitudes $\boldsymbol{\varphi}_{\mathrm{WGS}}$ parallel to the equator at 0° and longitudes $\boldsymbol{\lambda}_{\mathrm{WGS}}$ perpendicular to latitudes, running from the north to the south pole. Both measures are provided in degrees, whilst longitudes north of the equator are described by positive values. The central meridian in Greenwich, UK marks the longitude of 0°. The altitude of the position with respect to the reference ellipsoid is provided in meter (z_{WGS}). A fourth dimension, measured clockwise from $\boldsymbol{\varphi}_{\mathrm{WGS}}$ is used to describe the orientation of the position, commonly known as heading σ_ζ, where 0° refers to pointing north [163]. Within the ETSI ITS G5 standards, the reference position of an ITS-S ζ (φ_ζ, λ_ζ) refers to the ground position of the centre of the front side of the bounding box of the ITS-S, as depicted [57].

LTP As the calculation of distances relative to a certain position on the ellipsoid is challenging, a Local Tangential Plane (LTP) can be used to employ a Cartesian coordinate system $\{x_{\mathrm{LTP}}, y_{\mathrm{LTP}}, z_{\mathrm{LTP}}\}$ within a confined region [228], as depicted in Figure 5.1. Although somewhat similar to the Universal Transverse Mercator (UTM) projection, where calculations can be performed within a Cartesian coordinate system, the origin of the LTP coordinate system is located at any arbitrary point on the reference ellipsoid. The concept of LTPs makes use of the shape of the ellipsoid, which can be approximated as a flat surface for short distances: calculations on a LTP are based on geodesics on the ellipsoid, with a maximum error of 1 nm over a distance of 420 m [112, 132]. This error dimension is negligible in the context of V2X communication and sensor data fusion. It should be noted that since a LTP defines a right-hand Cartesian coordinate system, an orientation of $\theta_\zeta = 0°$ refers to east ($\sigma_\zeta = 90°$) in the WGS84 system, as depicted in Figure 5.1. LTP systems are often referred to as East, North, Up (ENU) coordinate systems, as the x_{LTP} and y_{LTP} axes are always aligned with Easting and Northing.

ISO 8855 The system introduced by the ISO 8855 standard is employed to describe the dynamics of a vehicle. The Cartesian reference frame $\{x_\zeta, y_\zeta, z_\zeta\}$ is depicted in Figure 5.1. The origin of the system is located at the vehicle's centre of mass. A rotation about any of the three axes mainly describes the current dynamic state of a vehicle. κ defines the roll of a vehicle. The pitch β is defined by a rotation about the y_ζ axis. The driving direction of a vehicle is determined by the yaw-angle ψ as a rotation about the z_ζ axis [42].

5.2. Data Frames for Collective Perception

Most of the following explanations in this section have been partially taken or adapted from [107].

The content of any message type for *Collective Perception* is especially relevant from the perspective of the ADAS applications. Only if all data elements required by a fusion process are part of the developed message format, the transferred information can be utilised. The following sections introduce dedicated data containers required by the concept of *Collective Perception*. Whenever applicable, already standardised variables from the CDD [83] are used.

5.2.1. Originating Vehicle Container

For data fusion and plausibility purposes, the received sensor data has to be related to the ITS-S disseminating the information. This ITS-S is also referred to as the *Originator*. Albeit a CAM already contains the position and the dynamic state of a vehicle, the *Originating Vehicle Container* is the essence required for relating the sender to its sensed objects as well as to perform the coordinate transformation as described in section 7.2. Figure 5.2 depicts all relevant data elements of the *Originating Vehicle Container*. As for the CAM, the *Generation Delta Time* describes the global timestamp corresponding to the provided *Reference Position* measurement. This variable describes the global position of the ITS-S, by providing the latitude, longitude and altitude as well as the corresponding 2σ ($\approx$95 %) confidence level

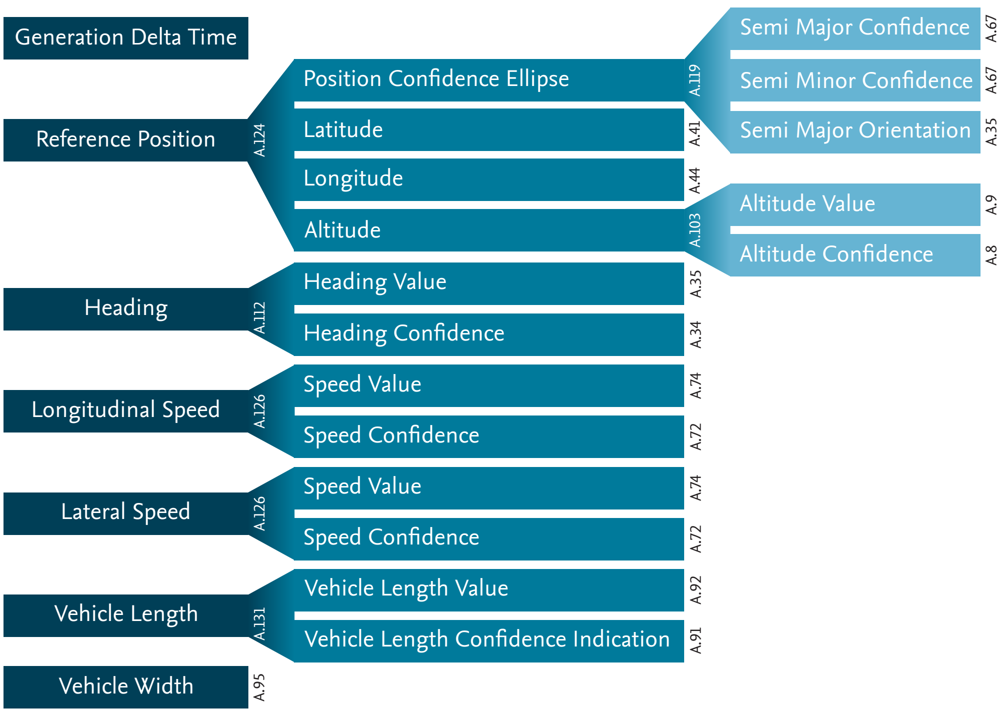


Figure 5.2.: Originating Vehicle Container. The tags refer to the corresponding existing variables already defined in the CDD [83]

of the position measurement, as provided by the GNSS receiver or localisation algorithm, e.g. Simultaneous Localisation and Mapping (SLAM) processes. As mentioned above, the provided position refers to the ground centre position of the bounding box of the ITS-S in the WGS84 system. The *Heading* data element describes the current orientation of the ITS-S on the WGS84 ellipsoid. To be able to calculate the relative and absolute speed of the detected objects with respect to the receiver, the longitudinal and lateral speed components within the ISO 8855 frame are provided as well. The sender's length and width are also provided to be able to describe the position of sensors mounted on the ITS-S.

5.2.2. Field-of-View Container

The sender's sensory capabilities can be described by utilising the *Field of View Container*, as depicted in Figure 5.3. Exchanging these capabilities allows for the derivation of a combined FoV, e.g. in situations where another ITS-S is able to provide information about an area into which a LoS does not exist.

The *Sensor ID* provides a data element for an arbitrary unique identifier for a sensor. The identifier is used to determine the sensor that has been used to perceive an object and never changes. The *Sensor Type* data element provides an enumeration of possible sensor types, e.g. Radar, Lidar, etc. without specifying the sensor's manufacturer. The sensor's properties are important for deriving the FoV of the sending vehicle. For this purpose, the *Sensor Position* variable describes the mounting point of the sensor with respect to the reference point of the originating vehicle, i.e. the centre front position in the opposite driving direction.The vertical (z-) component is omitted in the description of the sensor mounting point, as the height information is not provided by any ETSI message. The *Radius* data element simply defines the range of the sensor. As some sensors, such as rear- or side-mounted Radar sensors can have an angled mounting point, the *Opening Angle* variable further describes the orientation of the sensor's frustum with respect to the ISO 8855 coordinate system. From the sensor's perspective, the *Begin Angle* variable always defines the right-hand side boundary of the sensor's frustum.

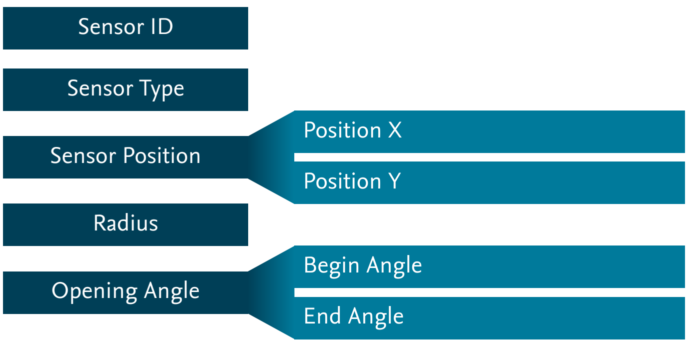


Figure 5.3.: Field of View Container

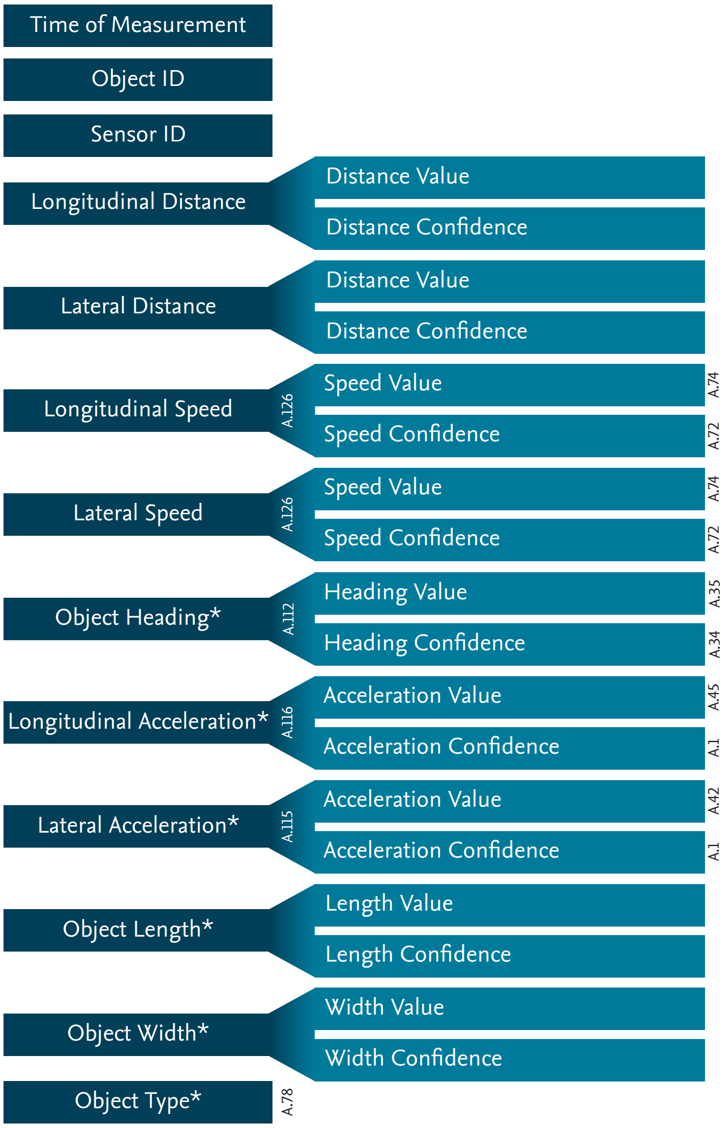


Figure 5.4.: Perceived Object Container (* indicates optional data elements)

5.2.3. Perceived Object Container

The *Perceived Object Container* is used to describe an object perceived by a sensor from the perspective of the sending ITS-S. Figure 5.4 lists the contained variables. The *Time of Measurement* provides a time offset with respect to the provided *Generation Delta Time* timestamp for temporally aligning the sensor data to the provided sending vehicle's position. This information is required by the data fusion processes to determine the resulting prediction horizon for this object. The *Object ID* is a unique random identifier assigned to the measured object. As long as the sending vehicle continuously assigns new sensor measurements to this object, i.e. in case it is able to track the object, the ID value remains constant. As such, a fusion result for consecutive measurements is proposed. To relate the object to the sensor that provided the measurement, the *Sensor ID* is used in conjunction with the corresponding data element of the *Field of View Container*. The relative distance from the sensor's mounting point to the object is provided by the *Longitudinal* and *Lateral Distance* variables. The sensor's measurement inaccuracies are also provided in a 2σ environment. The *Lateral* and *Longitudinal Speed* variables follow the same convention for describing the absolute speed of an object. In the same manner, the optional *Lateral* and *Longitudinal Acceleration* components may be provided as well, in case the disseminating vehicle's tracking algorithm is capable of providing acceleration estimates. Depending on the sensory capabilities of an ITS-S, the dimension of an object may be determined. For this purpose, the *Object Length* and *Object Width* variables are provided. In the case of an already existing measurement of an object's dimensions, the *Heading* may be provided as well, since the information about the relative orientation of the object with respect to the sending vehicle can be combined with the sending vehicle's heading to calculate the object's orientation on the WGS84 ellipsoid. However, it should be highlighted that for special vehicles, for which their width may exceed their length, this variable may be ambiguous. If the tracking algorithm of a sensor is capable of providing estimates about an object's acceleration, they may be provided as well. In case of the sending vehicle being able to classify a perceived object, e.g. by means of a camera, the *Object Type* data element provides a corresponding enumeration.

5.3. Message Types for Collective Perception

Most of the following explanations in this section have been partially taken or adapted from [104].

To realise the concept of *Collective Perception* within the ETSI ITS G5 framework, the identified containers in section 5.2 can be combined in two manners: One option is the definition of a new message format, containing only those variables required by the data fusion process, optimised towards the resulting payload size. Another option is to append these variables to an existing message format, such as the legacy CAM, to increase backward compatibility and to increase the efficient utilisation of the communication channel. Hence, the following sections first introduce these two approaches for accommodating the containers identified in section 5.2 and second, review the challenges of both approaches.

5.3.1. Environmental Perception Message

The new message format introduced as part of this thesis is called *Environmental Perception Message (EPM)* and essentially consists of the containers introduced in section 5.2. The overall message structure is depicted in Figure 5.5. Appendix A.1 outlines the corresponding

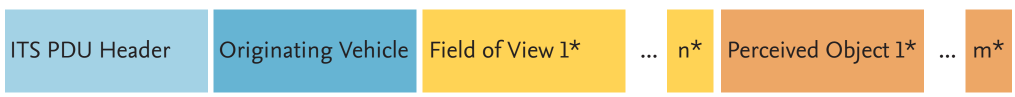


Figure 5.5.: Message structure of the Environmental Perception Message (* indicates optional containers)

ASN.1 definition of the message. As for any message disseminated within the ETSI ITS G5 framework, the *ITS PDU Header* identifies the station-ID as well as the message type of the payload. The mandatory *Originating Vehicle Container* is used for describing the current position and dynamic state of the disseminating vehicle, as described in section 5.2.1. The description of local perception sensors can be added to the EPM, by adding the *Field of View Container*. If the disseminating vehicle is currently able to perceive objects, the *Perceived Object Container* may be added to keep the resulting message size within limits. To allow for the scalability of the message concerning the number of attached sensors as well as concerning the number of described objects, the last two container types are optional. The maximum number of either container type to be added is restricted by the MSDU.

By employing optional containers, the message is enabled to breathe, i.e. change in size with respect to the amount of conveyed information. Figure 5.6 displays the resulting message sizes[1] after ASN.1 UPER encoding of the message type depicted in Figure 5.5 with respect to the number of attached *Field of View* and *Perceived Object Containers*. The minimum message size, i.e. when only the *Originating Vehicle Container* is present, results in an encoded size of 37 Bytes. Upon adding both container types, the message size increases. As these container types both include optional variables themselves, the message size may vary as depicted. The maximum encoded size of 709 Bytes results, when all *Field of View* and *Perceived Object* containers are added and all optional variables of every container are utilised. The average[2] size increase for every added *Field of View Container* is about 9 Bytes.

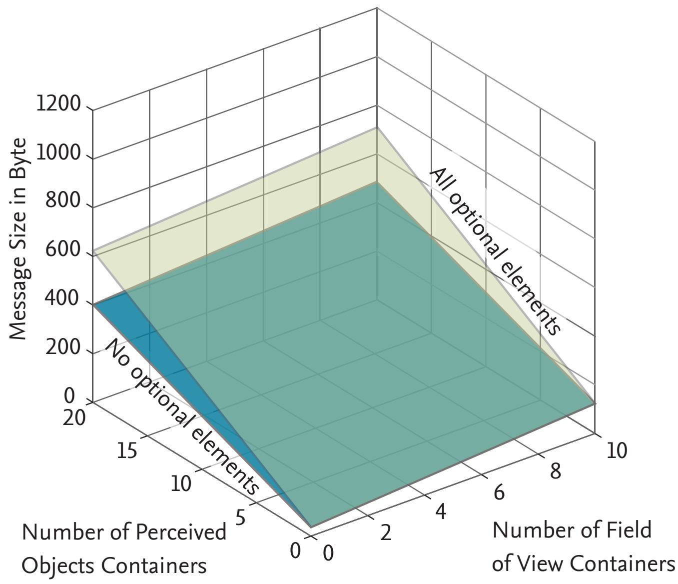


Figure 5.6.: Message size of the Environmental Perception Message with respect to the number of included *Field of View* and *Perceived Object Containers*

1 It has to be noted that the message size is a discrete value. The depicted (continuous) planes are displayed for visualisation purposes only.
2 Due to the bite alignment of ASN.1 UPER, the added size per container may vary.

The average increase for every added *Perceived Object Container* is about 19 Bytes without optional variables and 29 Bytes including all optional variables. The provided message sizes represent the size of the payload of a Geo Networking (GN)-packet as depicted in Figure 2.4, not including headers added by the consecutive layers.

5.3.2. Extending the Cooperative Awareness Message

As an alternative to a novel message format, the extension of already existing ETSI ITS G5 messages may be considered. Since sensor fusion processes require periodic and frequent (measurement) updates about the objects in the vehicle's vicinity [16, 251], the periodically generated CAM represents a suitable candidate for accommodating the required containers for *Collective Perception*. Figure 5.7 depicts the possible extension of the legacy CAM format, which has been detailed in section 2.2.1. For CAMs disseminated by a vehicle, the *Originating Vehicle Container* may be omitted, as all of the data elements of this container are a subset of the CAM's *Basic* and *Basic Vehicle High Frequency Container*. Infrastructure components (e.g. RSUs) may also be equipped with sensors, to also share information about its perceived objects [178]. CAMs sent by a RSU, however, do not include the *Basic Vehicle High Frequency Container*. Hence, the dynamic state variables of the sender are not available and have to be inferred on the receiver's side. However, the relevant position information required to transform the data of the RSU's perceived objects into the recipient's local reference frame are provided as part of the *Basic Container*.

As stated in the description of the EPM in section 5.3.1, the number of *Field of View Containers* and *Perceived Object Containers* is variable, limited by the MSDU only. The resulting message sizes with respect to the number of added containers are displayed in Figure 5.8. The minimum message size is 44 Bytes as opposed to the minimum size of the legacy CAM of 42 Bytes. The 2 Bytes size difference in the resulting transfer syntax is required to accommodate the extension markers for the added containers. As the legacy

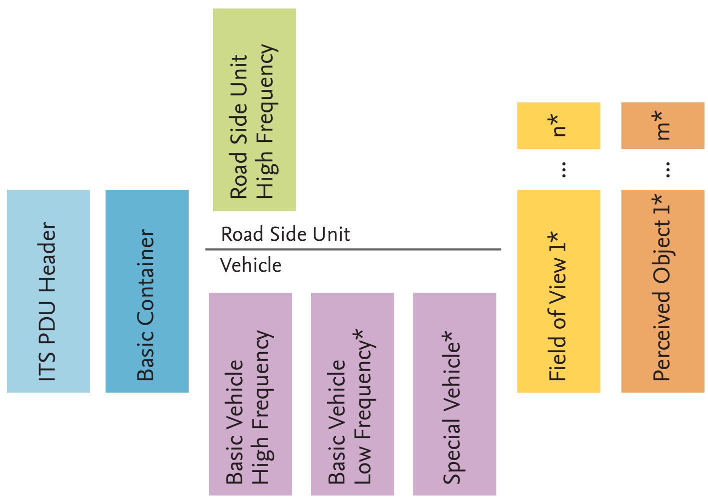


Figure 5.7.: Message structure of the extended CAM (* indicates optional containers)

CAM contains several optional containers and variables itself, the resulting message size is much larger compared to the EPM presented above.

The main contributor to the large size difference, when comparing the EPM to the extended CAM, however, results from the included *Basic Vehicle Low Frequency Container*, which contains the path-history.

5.3.3. Review of Message Formats and Reference Frames

Both approaches for realising *Collective Perception* within the ETSI ITS G5 framework are viable solutions with specific strengths and weaknesses which are discussed in the following paragraphs.

Message Format On the one hand, a new message format offers the possibility to freely design the structure and the included variables for optimising the resulting payload size with respect to the functionality and tentative network constraints. On the other hand, it has to be analysed whether the communication technology is capable of accommodating an additional message without interfering with the existing standards. Since the standard messages, such as the CAM and DENM are already broadcast on the ITS G5-CCH, a thorough analysis has to determine whether the utilisation of a separate channel for the purpose of transmitting the EPM should be adopted. Especially when taking the potentially available higher data rate of 12 Mbit/s at the ITS G5 SCH2 as opposed to 6 Mbit/s in the ITS G5 CCH into account, the utilisation of a second channel for a new message format for *Collective Perception* may be considered.

Furthermore, the question whether a new message format should be preferred over an extended CAM is also related to the question of how backward compatibility is provided. At

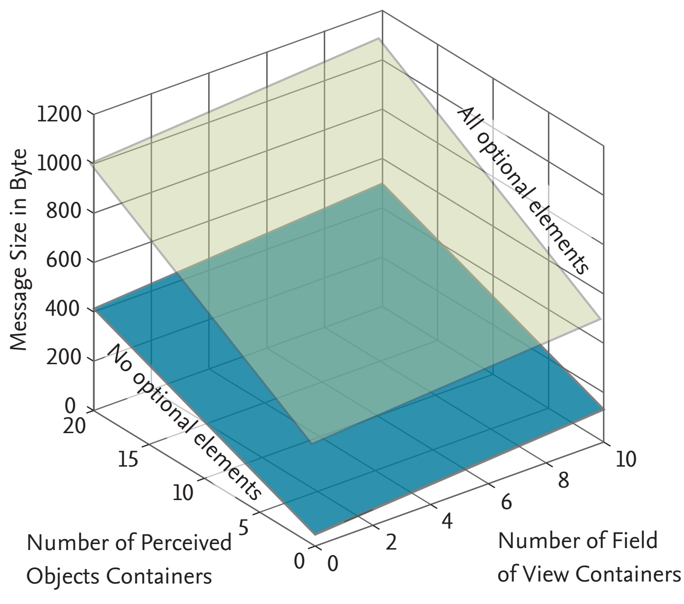


Figure 5.8.: Message size of the extended CAM with respect to the number of included *Field of View* and *Perceived Object Containers*

the time *Collective Perception* might be introduced to the market, it is reasonable to assume that there will already be a significant number of ETSI ITS G5 enabled vehicles on the road, capable of transmitting CAMs and DENMs. If a new message format for *Collective Perception* is introduced, these vehicles will not be able to decode this message. Instead, the effective usability of the communication channel for these kind of vehicles will be reduced. Due to the included ASN.1 extension markers ('...'), a CAM addendum of the required containers for *Collective Perception* provides backward compatibility without significantly reducing the effective channel utilisation.

Nonetheless, extending the CAM as proposed in section 5.3.2 brings along the problem of an increased message size. The maximum size of the transfer syntax of a CAM without adding any containers for *Collective Perception* is already 412 Bytes. The addition of any other container not only increases the message size even further but also demands for the introduction of an inclusion management, as it already exists — to some extent — for the different containers of the legacy CAM. To keep the resulting size of the transfer syntax within limits and to allow for the extension of the CAM with containers other than those required for *Collective Perception*, the inclusion management for the cooperative awareness service becomes rather complex. Although the footprint of the header overhead is reduced in case the CAM is extended, the resulting packet size is rather large. This, in turn, increases delays and the likelihood of packet collisions [51, 135]. At the same time, channel congestion increases, the longer the channel is kept in the *busy* state. Since channel utilisation within the ETSI ITS G5 standards is mainly controlled by DCC mechanisms, the effect of different DCC implementations on the principle of *Collective Perception* has to be studied.

Amongst others, the corresponding analyses regarding network constraints are presented in chapter 6.

Reference frames A well-defined reference frame has to be utilised, when exchanging sensor data between ITS-Ss. Otherwise, the data cannot be related to the current position of the receiver. From here, two approaches for defining the required data elements to be included as part of a *Collective Perception* message have to be differentiated: The first approach is based on using a global coordinate system only, also for the description of the perceived objects. The transmitting vehicle may calculate global WGS84 positions for perceived objects which are included in the message. The benefit of this approach is that since the sensor data is described in the same reference frame as the receiving ITS-S, the position of the transmitting ITS-S does not need to be provided. However, the only reliable connection between the sender's position and its sensor data would be the unique ID of the ITS-S. This information would have to be gathered from the latest received CAM which does not correspond to the data used for calculating global positions of the sensor data. Furthermore, in case a transmitter of an EPM can be matched to one of the sensor objects directly perceived by the host vehicle, GNSS measurements may be excluded from the coordinate transformation process — therefore increasing the accuracy of the received sensor measurements.

The second approach utilises a description of the objects within the transmitting vehicle's ISO 8855 coordinate system. This information can only be related to the receiver, when the position of the transmitter is also provided. Although connected to additional overhead, the second approach seems preferable from the perspective of sensor data fusion processes, as the inherent inaccuracies may be provided independently. Furthermore, in case a separate message is used for *Collective Perception*, updates about the disseminating vehicle are provided more frequently, i.e. by a CAM and by the message format for *Collective Perception*. It might be argued that even if WGS84 positions are calculated for the sensor objects, the sender's position may still be provided as well. However, encoding of the introduced distance type for a description within the ISO 8855 system only takes up about 8 Bytes as opposed to about 13 Bytes (including confidence indication values) when using the global position data types A.41, A.44 and A.119 from the ETSI ITS G5 CDD [83].

5.4. Message Generation Principles

Closely related to the discussion of an appropriate message format for *Collective Perception* is the definition of generation rules. The specification of these rules is subjected to a trade-off between the requirements of the data-fusion algorithms and the limitations of the IVC network [107]. From the perspective of data-fusion processes, frequent measurement updates about objects are required as often as possible in order to reduce the error of the object prediction and hence to increase the quality of the fusion result. From the perspective of the IVC network, however, the resulting network load should be as small as possible — hence less frequent updates and smaller message sizes are preferable.

The following principles set the framework for the generation rules for both the EPM or the extended CAM and have been published in [107]. Each of the principles are addressed in the subsequent chapters of the thesis.

5.4.1. Beaconing

ITS-Ss capable of *Collective Perception* should indicate this ability on a regular basis to other ITS-Ss located within the communication range. This indication may be performed by cyclically including the corresponding *Field of View Container*, e.g. at a rate of 1 Hz. Since the sensory properties of an ITS-S do not change, the *Field of View Containers* do not need to be included in every message, thereby reducing the message size. Hence, in the worst-case scenario, an ITS-S which has just entered the communication range of another ITS-S has to wait for 1 s before being able to relate the received object data to the sensor source. Even if an ITS-S does currently not perceive any objects to be transmitted, the *Field of View Containers* should still be transmitted either as part of an EPM or as part of of an extended CAM at the beaconing frequency.

Section 6.5 provides the results of several extensive simulation studies, in which the *Field of View Containers* were added at a rate of 1 Hz. The resulting message sizes for a sample vehicle are presented along with an analysis regarding the resulting channel utilisation.

5.4.2. Objects to Include and Criticality

The concept of *Collective Perception* envisages the publication of all objects perceived by an ITS-S due its local perception sensors. However, as detailed in chapter 6, sharing sensor data imposes strict demands regarding the communication channel and data timeliness. Therefore, certain mechanisms have to be introduced that control the number of objects to be included as part of any *Collective Perception* message. Additionally, the higher the channel load, the smaller a message should be in order to reduce the occupied air-time of an ITS-S. However, an increased channel load is usually caused by dense traffic on the road — a situation where profound knowledge about a vehicle's environment is particularly important. Hence, when selecting the objects to be added to either the EPM or the extended CAM as part of the *Perceived Object Containers*, those objects exhibiting the highest dynamics should be preferred. This approach is consistent with the generation rules for the CAM, which are detailed in section 2.2.1: only if one of the defined filter criteria applies, a *Perceived Object Container* is added to either the EPM or the extended CAM for this object.

Section 6.6 provides the findings of a simulation study which analyses the influence of *Collective Perception* on the resulting channel load. Chapter 7 further specifies the relevant data to be included to be used as part of an object fusion framework.

5.4.3. Precedence

In case the legacy CAM and EPM are transmitted on the same communication channel, the prioritisation of the messages needs to be addressed. Whilst from the perspective of backward compatibility, the transmission of CAMs should be favoured, the most relevant data from the perspective of a sensor data fusion algorithm is already part of the EPM: the *Originating Vehicle Container* contains most of the information about the disseminating ITS-S's position and dynamics. Hence, a final decision about the message prioritisation has to be discussed as part of the standardisation process for shared sensor data. Whereas the standardised CAM provides information about the sending vehicle only, *Collective Perception* aims at informing neighbouring vehicles about objects in the vicinity of the sender.

Furthermore, a new format serves two distinct tasks: on the one hand, it is able to provide redundant data in case of an already sensed object. These redundancies, however, provide the basis for a more comprehensive and accurate description of the tracked objects. On the other hand, the message may convey complementary information: if an object has not yet been listed within the individual environment model of an ITS-S, it can be added to increase the FoV of the receiving ITS-Ss. In case of having received an object from an ITS-S located only from within the V2X communication range, the FoV can be extended even beyond the LoS. The description of an object within the message requires a minimum set of information in order to set-up a new object within the environment model. The amount of information that can be collected about an observed object, however, depends on the characteristics of the employed sensors.

Closely related to this discussion is the preferred methodology for accommodating the required data containers for *Collective Perception*: this thesis provides a comparison regarding the communication channel's capabilities of either handling both the CAM and the EPM or just the single extended CAM in the same channel. Again, the decision about the preferred mechanism has to be discussed as part of the standardisation process.

5.4.4. Data Source

The source of the sensor data to be transmitted as part of any *Collective Perception* message needs to be selected in accordance with the requirements of a prospective data fusion process. The object list (track list) provided by the ITS-S's environment model has been subjected to several low-pass filters and prediction models. Hence, simply transmitting the data from this object list results in a substantial prediction error and filter cascades within a receiving ITS-S's environment model. Furthermore, the work presented by Chen et al. indicates that the performance of a multisensor-multitarget data fusion process decreases, when each sensor performs its own tracking (track-to-track fusion) as opposed to a centralised tracking (sensor-to-track fusion) [33]. Therefore, the data transmitted should be as close to the original sensor data as possible. However, simply transmitting the original sensor data, e.g. raw data, is also not a viable solution, as this imposes very high requirements regarding data rates and transmission frequencies [244]. As a consequence, this requires a dedicated architecture for an environment model capable of storing and selecting the sensor data to be transmitted as part of a *Collective Perception* message as well as of fusing remotely received sensor data. Due to sensor data fusion algorithms relying on information about the accuracy of the provided data, a corresponding error propagation model is also required.

Chapter 7 presents an implementation of the EPM and legacy CAM in combination with a high-level object fusion framework. The implementation provides an error propagation model and an architecture for employing different sensor data fusion algorithms. However, this thesis does not implement different data fusion processes itself but rather presents a framework for performing further research in this area.

5.5. Summary

Based on the findings of the systematic literature review provided in the previous chapter, this chapter presents the concept of *Collective Perception*: a holistic approach for sharing sensor data between traffic participants. For this purpose, the requirements resulting from the communication stack as well as from the applications eventually employing remote sensor data are presented.

At the core of the concept stands the definition of the data to be exchanged. For this purpose, three different data containers are introduced: the *Originating Vehicle Container* provides information about the ITS-S disseminating the message for sharing sensor data. The variables encapsulated in this container focus on providing the information required by the coordinate transformation processes, without further overhead. The *Field-of-View Container* provides the variables necessary to describe the sensory capabilities of an ITS-S.

The *Perceived Objects Container* provides a description of the detected objects. The container thereby takes different measurement principles of the sensors into account, as not all variables need to be provided. Whenever applicable, already standardised variables are used by the data containers.

As a next step, these containers are combined to propose a new message format for *Collective Perception*: the Environmental Perception Message. This message type represents a collection of these containers, whereas the *Field-of-View* and the *Perceived Object* containers may be added several times to include descriptions of multiple sensors and detected objects. Since remote sensor data should not be specific to a certain application, it needs to be transmitted frequently. Consequently, rather than using a new message format, the extension of the already standardised CAM by these containers is presented along with a comparison of the prospective resulting message sizes.

The proposed message formats and message generation principles are the result of two different perspectives, as detailed in the subsequent chapters: From the perspective of the ad-hoc network between the nodes, the content of the message is irrelevant, as only the transmission frequency and the air-time of the packets influence the channel utilisation. From the perspective of ADAS applications, remote sensor data should be provided as often as possible, thus contrasting the requirements of the former perspective.

6 Macroscopic Analyses

The presentation of the related work in chapter 4 demonstrates the relevance of the idea of sharing local sensor data between ITS-Ss. Several research projects already proposed mechanisms, such as possible message formats and data fusion algorithms to support prospective cooperative ADAS applications. However, several shortcomings have been identified: the proposed concepts either focus on the development of applications requiring shared sensor data or on the adaptation of existing sensor data fusion algorithms for remotely received sensor data. However, none of the related work focuses on the more general question of the potential of shared sensor data, i.e. the number of required ITS-Ss capable of *Collective Perception* for the technology to have a measurable effect. Closely related is the question of the feasibility of the concept: only if the existing communication technology is capable of meeting the requirements of shared sensor data, *Collective Perception* has a chance to be considered for standardisation.

As a consequence, chapter 5 derives the relevant data fields which need to be included in a message format for realising *Collective Perception* as part of the ETSI ITS G5 framework. These data fields have been identified to meet both network and sensor data fusion requirements. Furthermore, section 5.3 proposes both the extended CAM and the EPM as two possible viable message formats for *Collective Perception*.

This chapter focuses on the research questions identified in section 3.1 and hence represents the macroscopic, i.e. network-oriented analyses for the holistic concept of *Collective Perception*. The process of answering these questions requires an analytical framework which allows for in-depths analyses of different parts of the communication process. For this purpose, section 6.1 first provides an overview of the existing analysis environments. In a second step, section 6.2 introduces the simulation framework Artery — an extension for one popular representative of these analysis environments for dedicated modelling of the application layer of an ITS-S within a simulation environment. As any thorough analysis of *Collective Perception* requires realistic data input, Artery also provides the option of modelling local perception sensors as part of a traffic simulation environment, as presented in section 6.3. This simulation framework is employed for several simulation studies, which are introduced in section 6.4. To determine the potential of *Collective Perception*, section 6.5 presents the relevant findings of a corresponding extensive simulation study. To also analyse the feasibility of the concept in the context of an ETSI ITS G5 communication framework, section 6.6 presents the findings of the simulation study with the focus on comparing the two identified message formats presented in section 5.3 with respect to prospective limitations resulting from the employed communication technology.

The analyses presented in this chapter are considered *macroscopic*, as the scope of the analysis focuses on the VANET between the vehicles. Although each vehicle in the presented simulation studies is modelled individually, it is assumed that every vehicle maintains an environment model capable of processing local perception sensor data for providing the content of the *Collective Perception* message formats. The analysis focusing on the requirements from the perspective of a vehicle rather than the VANET is presented in chapter 7. Most of the work presented in this chapter is primarily based on the following publications: [94, 104, 105, 108, 183, 214, 215].

6.1. Macroscopic Analysis Environment for V2X Applications

When analysing vehicular communication technologies, a common challenge is the lack of a sufficient number of communication partners. Realistic field-tests in this context, such as the simTD and Ko-FAS projects, have proven to be challenging and comparatively costly [12, 252]. The overhead of getting the systems of different stakeholders within these projects running is a time consuming process, especially if parts of the research focuses on a very specific topic which requires multiple parameter variations and a very large number of communicating vehicles. Further challenges such as non-optimised antenna characteristics for a vehicle, limited repeatability, time consuming tests, restricted debugging possibilities, the lack of the possibility of comparing results, etc. pushed the development of specific simulation frameworks for VANET analyses.

Different frameworks with differing approaches for modelling both vehicle mobility and communication exist. Section 6.1.1 provides an overview of these approaches and details the framework selected for the analyses presented in this chapter. As the analysis of *Collective Perception* requires the generation of new message types in combination with different parameter settings of the communication stack, section 6.2 presents an extension to the selected framework for explicitly modelling the facilities and application layer of an ITS-S.

6.1.1. Vehicular Ad-hoc Network Analysis Environments

Compared to common communication networks, where the nodes are either static, e.g. computer terminals or servers, or move at a certain speed within a cellular network, e.g. a cell phone in a car, VANETs exhibit several special characteristics. The nodes within a VANET move on a complex road topology which in turn affects the network characteristics. Furthermore, the number of nodes and their speed distributions may change rapidly, i.e. when a vehicle approaches a crossroad. Additionally, the network is subjected to a fast time-varying channel as buildings and other obstacles may reduce the communication range significantly, especially in urban scenarios [150, 202]. As a result, the modelling of the node mobility needs to be as realistic as possible.

To be able to analyse VANETs with the help of simulation tools, two concepts have to be differentiated: first, the mobility of the ITS-Ss and second, the ad-hoc network existing between them. Depending on the research question, this distinction may be an invitation to abstract either perspective albeit at the cost of over-simplifying reciprocal influences [206]. However, dedicated simulation frameworks exist for both concepts, each with specific strengths and weaknesses. The following two paragraphs first introduce different approaches and simulation frameworks for modelling node mobility and ad-hoc networks. The third paragraph describes the selected simulation environment for the analyses presented in this chapter.

Modelling Node Mobility

The generation of node mobility and its application for VANET simulation may be extended to a chapter all by itself. The following paragraph merely provides an overview of the existing methods. A comprehensive review of traffic simulations and its challenges is provided in [24]. Four approaches for modelling traffic have to be differentiated:

Macroscopic models consider the traffic flow in a larger constrained area, such as a city, county or state [24]. The purpose of these simulations is the determination of global state variables such as the average speed or traffic density on certain roads. Due to publicly available traffic flow measurements and Floating Car Data (FCD), e.g. provided by public authorities, calibration of simulation models is comparatively simple. The subject of interest of *macroscopic* traffic simulations is not the individual vehicle or passenger within the network, but the traffic flow on a higher level. Therefore, instead of modelling each vehicle individually, *macroscopic* traffic simulators assign traffic flow variables to the edges of a street network [24]. A representative of a commercially available *macroscopic* simulator is VISUM [226].

Mesoscopic models make use of the global parameters of a *macroscopic* model and apply these to a group of vehicles which are modelled in more detail. These kinds of models focus on the travel of clusters or groups of vehicles of interest within a large network without specifying each vehicle's behaviour and interaction at a higher level of detail [24]. *Mesoscopic* models are favoured, whenever a more detailed description of the traffic participants is required but rendered infeasible due to resource requirements, coding overhead or the size of the network [24]. A more recent development is the use of *hybrid* simulation models, where a *mesoscopic* simulator is used for the majority of the road network and only a certain part of the network is modelled on a *microscopic* level. A representative for both a *mesoscopic* and *hybrid* simulator is VISSIM [230].

Microscopic simulations explicitly model each traffic participant individually. For this purpose, state variables are assigned to each vehicle within the simulation which change according to a set of individual models, governing the overall behaviour and interaction of the vehicle with others. The car-following model determines the behaviour of a vehicle with respect to other traffic participants, a lane-change model influences a vehicle's desire to change lanes and a route-choice model determines the order of the streets a vehicle will take to reach its destination [24, 137]. Additionally, infrastructure components such as traffic-lights and speed signs are also considered by the traffic participants. As a consequence, most simulators allow for the manipulation of the behaviour of individual vehicles, e.g. change the speed or alter its current route. *Microscopic* traffic simulators may also be employed to measure global traffic parameters such as average lane speed and traffic flows as provided by *macroscopic* models. However, whilst these parameters are the variables of the simulation model of *macroscopic* simulators, they can be computed from aggregated measurements in *microscopic* models as a result of the interaction between the traffic participants [24]. The challenges of *microscopic* models compared to both *macro-* and *mesoscopic* models are the model calibration and the need for a detailed road network. Representatives of common *microscopic* traffic simulators are commercially available frameworks such as VISSIM [230] and AIMSUN [29] as well as the open-source framework Simulation of Urban Mobility (SUMO) [136].

Although also modelling each vehicle individually, *sub-microscopic* simulations focus on representing several vehicle components in more detail rather than abstracting to dynamic state variables. Consequently, the focus of *sub-microscopic* models is not the interaction of multiple vehicles but the representation of a single vehicle as a complex system. These models are mainly used for the design of a vehicle's driving dynamics or for testing a vehicle's ECUs as part of a Software in the Loop (SiL) or Hardware in the Loop (HiL) simulation environment [149]. Numerous commercial simulation environments are available, such as Virtual Test Drive (VTD) [102] or CarMaker [28].

Modelling Ad-hoc Networks

For the same reason mobility simulators are favoured over operational field-tests with several hundred vehicles when it comes to developing connected ADAS applications, dedicated network simulators are used for analysing large scale networks with multiple network nodes. A vast number of network simulation frameworks exist, most of them very specific to a certain type of network. For VANET simulations, the multi-purpose open-source network simulators ns-2/-3 [34, 113] and the Objective Modular Network Testbed in C++ (OMNeT++) [223] are commonly used in the research community. Both of these simulators employ an event-based priority queue. Enqueued events are processed in scheduled order. As a result, the simulation time is advancing to discrete points in time, governed by these enqueued events [223]. This mechanism meets the requirements of a network model, where the actual time of the data transfer, e.g. the air-time of a packet between nodes is very small compared to the computation overhead of transcoding a packet. Simultaneously, the simulation progress is not bound to wall-clock time but may advance independently.

The simulation frameworks provide interfaces for high-level programming languages, such as C++, thereby rendering them as ideal candidates for further custom extensions [186]. Furthermore, node mobility is supported — a crucial requirement for VANET simulations. Additionally, widely used extensions, such as the INET-framework [222] for OMNeT++ are publicly available which are thoroughly tested and proved by the research community. INET closely resembles the OSI model and offers several protocol and physical layer implementations of different communication technologies. The open-source nature of these frameworks increases comparability of simulation results which is of particular interest in the research community. For some of these simulation frameworks, commercial versions are also available.

Combining both models

The former two paragraphs highlighted the need for detailed simulation models for both vehicle mobility and the ad-hoc network between the vehicles. When it comes to analysing *Collective Perception*, the number of detected objects plays a crucial role towards the resulting message size. Consequently, detailed modelling of the vehicles' surroundings is even more important.

For the simulation of VANETs, a combination of different simulation frameworks of both regimes seems favourable. Sommer et al. provide an overview of the possible realisations for combining realistic mobility profiles of vehicles with a network simulation environment. Four possibilities have been identified [205]:

Random Node Movement In its simplest form, movement of network nodes within a VANET could be random, i.e. based on a random-number generator. Whilst this approach is comparatively simple and may be improved by imposing a so-called *Manhattan Grid* as proposed by the ETSI [63], the node movement is still somewhat generic and does not resemble realistic trajectories as found in real life [35].

Real-world traces A simple solution to restrict the movement of network nodes to realistic profiles is to replay recorded real-world vehicle GNSS traces in the network simulation during runtime. However, this approach is limited to the number of available traces which are difficult (and expensive) to obtain albeit some traces are publicly available. Another drawback is the fixed scenario which cannot be altered to represent different traffic flows or vehicle densities.

Artificial traces As an alternative to real-world traces, microscopic traffic simulators may be employed to generate artificial traces. For this purpose, a road network is populated with vehicles within the traffic simulator and the corresponding trajectories are recorded to be replayed in the network simulator. This approach also addresses the issue of generating traces of the same scenario with different traffic flows or vehicle densities.

However, vehicle connectivity and node mobility also influence each other: albeit characteristic mobility of network nodes as found in vehicular traffic has an effect on the ad-hoc network between the vehicles, the introduction of inter-vehicle communication in turn also effects the mobility of the nodes. As outlined in section 2.3, future vehicles will be both automated and cooperative due to communication. As a consequence, the trajectory of a vehicle may be changed due to communication compared to a scenario without it. Any of the three approaches presented above is incapable of changing the vehicle trajectories due to communicating vehicle applications. However, for analysing and testing cooperative ADASs, the algorithms running on the nodes in the network simulator need to be capable of manipulating the behaviour of the corresponding vehicles simulated in the traffic simulator:

Bidirectional coupling For providing detailed models of both node mobility and the ad-hoc network between these nodes, whilst at the same time being capable of influencing each other, both dedicated simulators are coupled at runtime. Although this raises the challenge of synchronising both simulation frameworks, Sommer et al. show that bidirectional coupling of these two simulator types results in vastly differing findings compared to simply replaying recorded traces [204]. Several differing implementations for a bidirectionally coupled VANET simulation framework exist. Martinez et al. and Sommer et al. provide a comprehensive review of the available solutions [150, 205]. Whilst some research institutions developed proprietary, disclosed solutions, several open-source projects such as Veins [203], VSimRTI [195] and iTetris [190] are available.

The large research community associated to Veins is mainly responsible for the ongoing development of the framework for several years by now. The bidirectional coupling of a dedicated traffic and a dedicated network simulator, both being open-source projects themselves, provides the ideal basis for analysing *Collective Perception* as part of extensive simulation studies. Furthermore, the available numerous well-tested extensions, as well as the increasing number of scientific publications based on Veins, rendered this candidate as the chosen framework for the analyses presented in this thesis.

6.1.2. Veins

As described above, Veins is an open-source simulation framework for the analysis of different aspects of VANETs. At the core of the framework stands the bidirectional coupling of the microscopic traffic simulator SUMO and the network simulator OMNeT++ as depicted in Figure 6.1. For this purpose, Veins makes use of the Traffic Command Interface (TraCI) protocol provided by SUMO [233]. At the start of a simulation run, a Transfer Control Protocol (TCP) connection is established between both simulators. Veins registers itself as a subscriber to certain events, such as to vehicles entering or leaving the road network as well as to the traces of the currently active vehicles. At a regular interval of

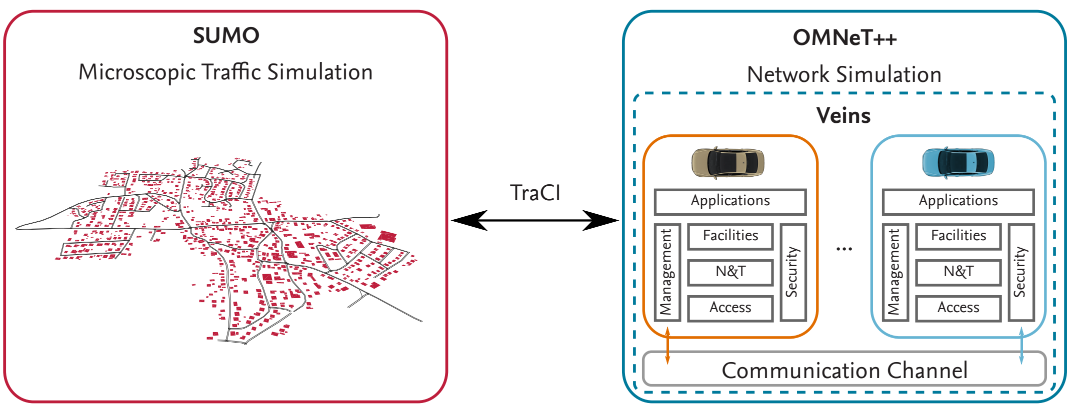


Figure 6.1.: Interaction between microscopic traffic and network simulation

100 ms (simulation time), Veins sends a command to SUMO to provide the traces of the next simulation step before commencing with the corresponding calculations within the network simulator. During the execution phase of the network simulation, i.e. when SUMO waits for the command to generate the next traces, the algorithms running on the nodes within OMNeT++ might trigger a change of the behaviour of several vehicles, e.g. a lane- or a speed-change. As a consequence, the corresponding TraCI command is transmitted to SUMO, where it is buffered to be respected at the next simulation step [204]. In this manner, the synchronisation of both simulation frameworks is ensured. Depending on the available computing resources and the number of simulated vehicles, the framework is capable of executing faster than wall-clock time.

For every existing vehicle within SUMO, a corresponding network node may be instantiated within OMNeT++, as indicated in Figure 6.1. Especially at the time of market introduction of IVC, not all vehicles will be equipped with communication capabilities. Consequently, mixed traffic situations are of particular interest, especially for the analysis of the *Collective Perception* mechanisms introduced in chapter 5. For this purpose, Veins is capable of equipping only a fraction of the simulated vehicles in SUMO with communication capabilities. For every communicating vehicle, Veins introduces a complete IEEE 802.11p protocol stack, including the physical layer modelling taken from the MiXiM project [240]. Several adapted radio propagation models for the vehicular context are also provided. A two-ray interference model considers ground reflection effects characteristic for radio propagations on unobstructed road segments [207]. A second model additionally takes obstacle shadowing into account. For this purpose, building polygons existing in SUMO are imported to OMNeT++ at the beginning of a simulation run. Afterwards, these polygons are considered by a calibrated radio propagation model in case of obstructed LoS communication [202]. For the higher layers of the protocol stack, Veins provides parts of the American DSRC / WAVE protocol stack, such as channel hopping and WAVE Short Message (WSM) handling [49].

Although Veins already addresses many aspects of VANET simulations, several shortcomings exist for the analysis of *Collective Perception*. First, an implementation of the European ITS G5 stack, including the standardised messages such as the CAM or DENM does not exist. Closely related is a missing implementation of DCC algorithms specific to the European standards which alters the transmission behaviour of an ITS-S significantly [48]. Second, although the application layer of Veins is exchangeable, integration of different or multiple applications for every simulated vehicle is cumbersome. Third, *Collective Perception* relies on the perception of a vehicle's environment by means of local perception sensors attached to these vehicles to both generate realistic message sizes and to test applications based on shared sensor data.

Aiming at resolving these shortcomings, this thesis introduces Artery, an extension to Veins.

6.2. Artery

Most of the following explanations in this section have been partially taken or adapted from [183].

Artery steps up to eliminate the aforementioned limitations of Veins concerning the modelling of vehicle applications and the ETSI ITS G5 communication stack in the context of VANET simulations. Subsection 6.2.1 first introduces the requirements for the extensions to Veins. Subsection 6.2.2 briefly introduces the implementation of the employed European protocol stack. The subsequent subsections 6.2.3 – 6.2.5 detail the implementation of Artery with the focus on independent ITS-S applications. As stated above, the analysis of *Collective Perception* requires the modelling of local perception sensors. For this purpose, section 6.3 details the corresponding implementations.

6.2.1. Requirements for a Modular Simulation Environment

State-of-the-art VANET simulation frameworks such as Veins are designed to deliver a high degree of flexibility and customisability, in order to be applicable for a wide range of use cases. However, as stated in subsection 6.1.2, Veins lacks the options of using the European communication stack and of equipping several vehicles with different (multiple) applications. Consequently, the development of Artery considered the following requirements:

Reusability The developed components should be generic for further use in different scenarios and settings.

Isolation As Artery is supposed to be used by a diverse user base, its structure should allow flexible development of novel functionalities in any one of the layers without the necessity of detailed knowledge in every layer.

Rapid prototyping The focus of the proposed framework is to assist the development and analysis of novel VANET applications. Therefore, code repetition should be avoided and common building blocks should help focusing on the development of application algorithms.

Extensible message formats Akin to already standardised messages like the CAM and the DENM, it should be possible to create and use custom messages for future applications, i.e. for *Collective Perception*. Hence, the framework should allow messages based on ASN.1, as well as OMNeT++'s native message format.

Familiarity Components and interfaces shall closely resemble related standard specifications and thus minimise confusions between the simulation model and the system specification.

Timing Delays introduced by packet buffering or congestion control restrictions should be taken into account.

Artery has to meet these requirements in order to broaden the applicability of VANET simulations beyond the questions solely related to communication protocols. The Application and Facilities layers of the ITS-G5 reference architecture shown in Figure 2.3 are resembled by Artery as depicted in Figure 6.2. Artery provides a flexible framework for the implementation of services (applications), containing the algorithms of a specific ADAS application. The underlying idea to Artery is to provide an extensive simulation framework for the development and testing of novel VANET applications. Essentially, Artery consists of the ITS-G5 middleware as well as of various services to be registered with the former one. With the introduction of a modular application layer, Artery also addresses developers and researchers specifically interested in functional aspects of VANET applications.

Artery itself consists of various components to model vehicles with operational ITS-G5 network stacks, as depicted in Figure 6.2. Each V2X enabled vehicle is equipped with a dedicated simulated network adapter originating from Veins. However, the MAC layer has been enhanced to also generate channel load measurements, which are the most important input data for the DCC algorithms provided by the ETSI ITS G5 implementation, called Vanetza [187]. Additionally, the MiXiM implementation of the physical layer has been replaced by the implementation provided by the INET framework [222]. On top of these components operates Artery's middleware, which acts as an abstraction and data provisioning layer for VANET applications, called services in Artery's terminology.

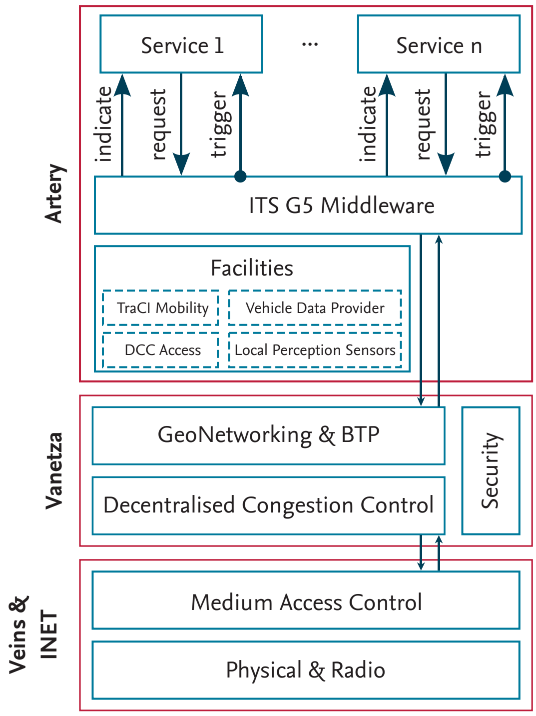


Figure 6.2.: Artery architecture

6.2.2. Vanetza

Vanetza resembles a stand-alone implementation of various components of an ETSI ITS-G5 protocol stack [184, 187]. It comprises GeoNetworking [55], BTP [56] as well as DCC [25, 73] and some security [185] mechanisms. As a result, the packet size modelling is adequate and conforms to the envisioned ETSI security mechanisms which introduces additional header overhead such as signatures and certificates. Although Vanetza has been designed to be used within OMNeT++ simulation models, it does not require OMNeT++ for its operation.

6.2.3. ITS-G5 Middleware

The key element of Artery is the ITS-G5 middleware, as depicted in Figure 6.2. It serves as the backbone for any Artery service, acting as an information hub and providing interfaces to further components. Upon initialisation of a node (i.e. insertion of a new vehicle by SUMO), the ITS-G5 middleware performs an initialisation process. As part of this process, Vanetza's GeoNetworking router in each vehicle is initialised with a station type and a network address. Additionally, the Facilities layer is initialised, as detailed later in this section.

Furthermore, specific services are created according to an external configuration file, which lists the required services for a group of vehicles. This feature enables the user to specify the services to be activated during the set-up process of the simulation, thus flexibly extending the functionality of vehicles without the need for recompilation, which speeds up working with simulations. It is also possible to specify the usage of a service for a specific vehicle or for a certain percentage of V2X-enabled vehicles only. This approach also allows for the development and comparison of different versions of a service side-by-side. As soon as services evolve, this becomes interesting for backward compatibility tests. Each service to be enabled is assigned a unique port number for addressing messages to applications active on the station. Closely resembling BTP operation, the port number is used by a port-dispatcher to route all incoming messages from the MAC layer to the corresponding service. Upon creation of a service, its initialisation procedures are called by the middleware. The final step of the initialisation process of the ITS-G5 middleware determines a random time offset within each update interval of the simulation and schedules an individual update-event for this vehicle, as depicted in Figure 6.3. This prohibits all vehicles from being updated at the same time, thus causing collisions on the channel, as all nodes would

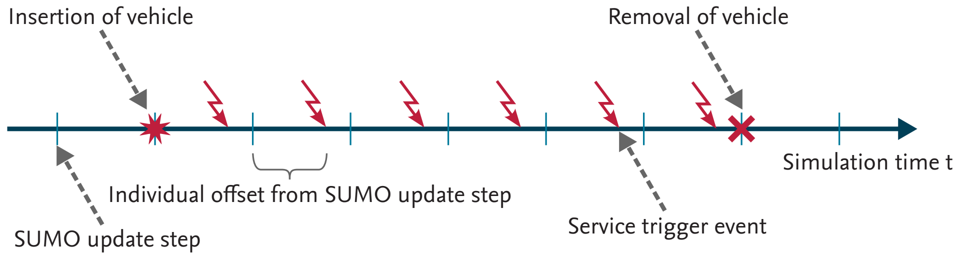


Figure 6.3.: Life cycle of an ITS-S within Artery

try to access the channel simultaneously. Hence, every vehicle is assigned a unique update-pattern, resembling the behaviour of real-life systems. Upon occurrence of an update event, the `trigger` method of each service is called, as indicated in Figure 6.2. This provides an entrance point for algorithms implemented as part of these services, e.g. an algorithm can be activated based on the vehicle's position or dynamic state.

What is more, the ITS-G5 middleware is responsible for routing messages to and from all services. As depicted in Figure 6.2, services use the `request` method provided by the middleware to pass messages to the lower layers, i.e. for transmission. Conversely, messages will be delivered to the service through the `indicate` method upon message reception. As listed in subsection 6.2.1, support for message development was one of the requirements for the implementation of the simulation framework: on the one hand, the architecture should be able to handle ASN.1-formatted messages in order to employ already standardised messages such as the CAM or DENM within the simulation environment. However, as these messages may not be sufficient to realise novel applications, the environment should also support the use of native OMNeT++ `cPackets` to assist rapid service prototyping. Therefore, the middleware can handle send-requests of both message types and encapsulates any passed message content from the service to the middleware into a GeoNetworking packet. After encapsulation, the packet is passed down layer-by-layer until it reaches the access layer for transmission.

6.2.4. ITS-G5 services

The services of the proposed Artery architecture resemble the application layer within the reference architecture. In order to create a service, the Artery framework offers a parent class which serves as a skeleton for any new service. One of the requirements for the implementation of the Artery architecture is to account for simple application development as listed in subsection 6.2.1. Being part of the OMNeT++ class hierarchy, every service can employ all of the out-of-box functionalities of OMNeT++, such as handling of events and collection of statistics. Furthermore, a service can be parametrised in the OMNeT++ configuration file containing the settings for simulation runs.

This design allows the user to view each service as a stand-alone application of a vehicle, incorporating the algorithms of a certain application, such as a Cooperative Adaptive Cruise Control (C-ACC). Furthermore, each service is responsible for sending messages required by the application as well as for handling those messages arriving at the service. This unique feature supports the creation of services as users can concentrate on application development. In addition, the user is supported in the development of messages, as abstract messages can either be specified with ASN.1 syntax or as an OMNeT++ `cPacket`. One example service provided by the Artery framework is the CA service which not only transmits CAMs according to the ETSI standard but also employs the ASN.1 message specification provided by [57]. Therefore, in case of already existing ASN.1 specifications, messages do not need to be redefined within the simulation environment.

As depicted in Figure 6.2, the parent class of any service also provides methods for receiving and sending messages. The `indicate` method is called by the middleware, when a respective message arrives at this layer and — based on the pre-assigned port number of the service — has been addressed to the corresponding service. Similarly, the `request` method is used to pass a message to the middleware, which hands it over to the MAC layer. Prior to passing a message to the middleware, the `request` is accompanied by further routing information such as the traffic class, transport type and destination port as specified by the ETSI `BTP-DATA.request` interface [56]. This information will be used within the middleware to set the control information for further message encapsulation.

6.2.5. Facilities

Artery also embodies elements of the Facilities layer depicted in Figure 6.2. For this purpose, each service is granted access to the methods provided by the separate facilities class of the Artery framework. As described in subsection 6.2.3, the middleware initialises the facilities for each vehicle. The class provides access to three different facility members which can be used by any service. The first facility, Veins' `TraCIMobility`, is used for retrieving information about a vehicle as well as for controlling its behaviour by using SUMO's TraCI protocol. Although most of the state information of a vehicle can be retrieved from this interface, some values such as the heading, yaw-rate and curvature are not readily available from SUMO.

However, the second facility component, the Vehicle Data Provider (VDP), is capable of providing this information by using values from prior simulation steps to calculate the missing state information. The Facilities layer also suits for providing an interface for local perception sensors, as detailed in subsection 6.3, which measurement data may be used by a service for creating *Collective Perception* messages.

The limiting resource in VANETs is the channel which all vehicles within the communication range try to access. Prior to message generation, applications have to take the current channel load into account. The fourth member of the Facilities-class therefore provides access to the finite state machine and scheduler of the DCC. In concordance with the CAM specification [57], the Cooperative Awareness service employs the provided DCC scheduler to control the CAM generation frequency.

6.3. Local Perception Sensors in Artery

Most of the following explanations in this section have been partially taken or adapted from [105].

Within the Veins framework, vehicles are only aware of the presence of other vehicles, if they receive a message, such as the periodically disseminated CAM, from neighbouring vehicles. It is up to the applications in the vehicles to interpret and to react to the received messages, e.g. by changing the lane due to a decelerating vehicle in front. Albeit Veins is capable of simulating mixed scenarios, in which only a limited number of vehicles are equipped with a network stack, communicating vehicles only know about the presence of other communication enabled vehicles — the presence of non-equipped vehicles, however, is not known to the vehicle applications.

As outlined in section 6.2, Artery introduces the option to equip vehicles with multiple (different) applications, called services. A missing element to implement currently existing

ADASs in the framework is the capability to attach local perception sensors such as a Radar or camera sensor to vehicles. With the introduction of local perception sensors, vehicles would be enabled to also perceive non-V2X-enabled vehicles.

Within this thesis, the introduction of a local perception architecture to the Artery framework is presented. The extension even allows for the flexible introduction of multiple local perception sensors to the vehicles. In order to perpetuate maintainability, the interconnection with the Veins framework is kept at a minimum. The perception system builds upon three key elements: the Global Environment Model (GEM), which acts as the backbone to the local perception system, the Local Environment Model (LEM) which is instantiated for every equipped vehicle and responsible for storing the detected objects within the perception range of the sensors, as well as the local perception sensors, which define the physical properties of the sensor.

6.3.1. Requirements and Architecture

The development of the local perception sensors within the simulation obeyed the following requirements to suit a large range of applications:

Scalability In analogy to the option of introducing different penetration rates for V2X enabled vehicles, the number of vehicles to be equipped with local perception sensors should also be variable.

Maintainability Since both Veins and Artery build the basis for the simulation platform, changes and updates should be compatible to the implementation of the perception system. Furthermore, in order to have all source code within one application, the perception system should also be implemented in OMNeT++ rather than within SUMO.

Visualisation When developing vehicle applications, it is important to be able to visualise the behaviour and the reactions of the road users. This also calls for an option to enable visualisation of the current perception range of the sensors of each vehicle within SUMO or within OMNeT++'s Integrated Development Environment (IDE).

Accessibility The developer of the services should be provided with a simple mechanism for retrieving information about the detected vehicles within the sensor range.

The corresponding local perception architecture within Artery as well as the interactions between the components are depicted in Figure 6.4. The encircled numbers within the Figure serve as guidelines and will be referred to in the descriptions of each component. Essentially, the framework builds upon three core components. Every vehicle equipped with local perception sensors maintains a specific sensor-set as well as a Local Environment Model (LEM). Every sensor-set consists of at least one sensor-component, defining its properties and providing mechanisms for retrieving objects within its perception range. The last component, the Global Environment Model (GEM), serves as the backbone of the perception system and maintains all objects within the simulation.

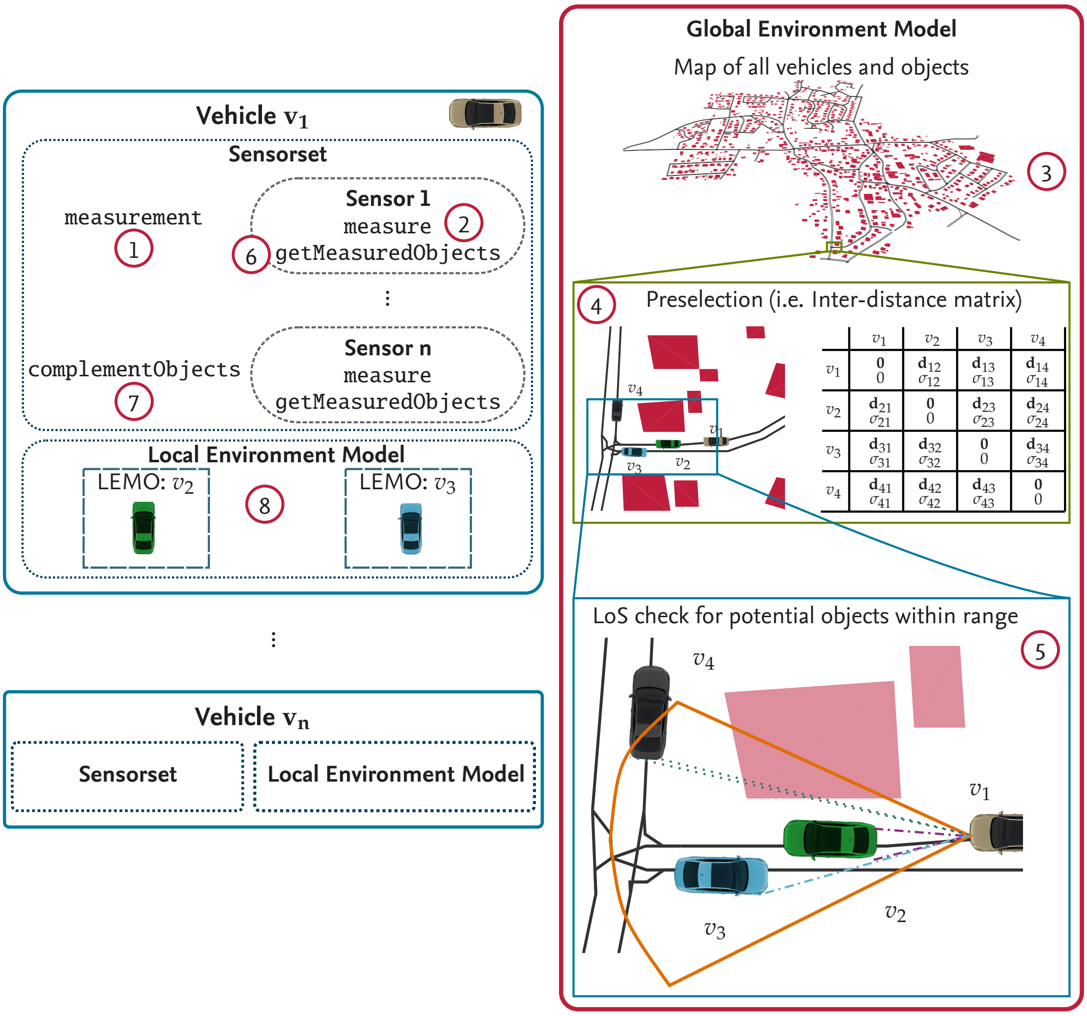


Figure 6.4.: Interaction between the components of the local perception system within Artery

6.3.2. Global Environment Model

The basis for the local perception system is the Global Environment Model (GEM), which acts as a global database for all objects within the simulation and therefore resembles a map of all objects within the simulation on a global scale (3 in Figure 6.4). Whenever a node is introduced, a so-called Global Environment Model Object (GEMO) is added to that database. A GEMO is linked to the `TraCIMobility` model of the vehicle within the simulation as well as to some further information required to describe the object, such as its geometric dimensions, to the attachment points of local perception sensors as well as to a list of vehicles that are currently able to perceive that particular GEMO. Whenever a vehicle changes its dynamic state due to a new simulation step from SUMO, the corresponding GEMO is also updated. The GEM acts as the backbone to the perception system within the simulation. The determination of the presence of an object within the perception range of a sensor is performed by the GEM.

Whenever a sensor performs a measurement to determine its perceived objects, it passes the geometric dimensions of its perception area to the GEM (1 and 2 in Figure 6.4). As a next step, the database of the GEM is queried to return the objects within the sensor's perception range. Due to the large number of vehicles within the simulation, a pre-selection mechanism determines the vehicles which are potentially located within the perception range of the sensor, based on the centre-point of each vehicle (4 in Figure 6.4). In order to account for the detection of those vehicles which corner-points are just within the perception range of the sensor, its range is temporarily increased by the diagonal distance from the centre-point of the vehicle to one of its corner points. For performance purposes, the database within the GEM offers three different mechanisms to determine the objects within the range: A so-called *inter-distance matrix* is updated at every main SUMO simulation step and stores the relative Cartesian distance $\mathbf{d}_{\rho\zeta}$ and direction $\sigma_{\rho\zeta}$ from every vehicle ρ to every other vehicle ζ within the scenario, as depicted in Figure 6.4. The second mechanism employs a spatial search algorithm based on the R-tree method [13] and the last method employs the intersection testing algorithms offered by the widely used boost-libraries [18]. Depending on the number of vehicles within the network, different pre-selection algorithms should be used. Whereas for a few vehicles, looping through the inter-distance matrix is the fastest solution, a medium number of vehicles is best selected by making use of the intersection-testing method. Due to the required generation of the search-tree at every major simulation step, the R-tree method is best used for a large number of vehicles.

After the pre-selection step has identified the potential vehicles within a sensor's perception range, LoS checks for all pre-selected vehicles are performed (5 in Figure 6.4). During the initialisation phase of the simulation, the polygon descriptions of the obstacles, e.g. buildings within SUMO, are also imported to the GEM database. When performing the check for LoS obstructions, at least one point of the selected vehicle within the perception range has to be within the LoS from the mounting point of the sensor. An obstruction occurs, whenever another vehicle or obstacle polygon is located within the direct path to a corner-point of a vehicle to the sensor's mounting point. In order to reduce computation time, the LoS check is terminated, whenever at least one of the four corner points of a vehicle, starting from the back of the vehicle, has a valid LoS to the sensor's mounting point. Step 5 in Figure 6.4 indicates a situation, where only vehicles v_2 and v_3 are located within a valid LoS to the sensor's mounting point on vehicle v_1. From the perspective of vehicle v_1, there is no direct LoS to vehicle v_4 which is therefore not enlisted in the LEM.

6.3.3. Local Environment Model

Whereas only one instance of the GEM exists within the simulation, every vehicle equipped with at least one local perception sensor creates its own instance of a Local Environment Model (LEM) (8 in Figure 6.4). The LEM acts as the database of all objects that are known to the specific vehicle. The LEM is part of the Facilities offered by the Artery framework and can therefore be accessed by any Artery service, as described in section 6.2.5. Whenever a measurement is performed by the sensor, the vehicles within its perception range are added as Local Environment Model Objects (LEMOs) to the database within the LEM, as depicted in Figure 6.5 for vehicles v_1 and v_5. In analogy to the GEMO, each LEMO is also linked to the `TraCIMobility` model that belongs to the observed vehicle. Whenever a vehicle is first measured by a perception sensor, i.e. the vehicle has not been sensed before by the measuring vehicle, a new LEMO is created for that particular vehicle.

Every LEMO consists of several circular buffers, each assigned to a perception sensor of a vehicle, as depicted in Figure 6.5. The buffers are responsible for storing the measurements of a perception sensor describing the state of an observed vehicle at the time of measurement. This allows for the creation of a history of measurements for a LEMO, whereas the length of the history, i.e. the number of measurements stored for each object corresponds to the dimension of the circular buffer.

There can be several LEMOs describing the same observed object in different vehicles, as depicted in Figure 6.5: vehicle v_2 is perceived by vehicles v_1 and v_5. Therefore, both observing vehicles maintain LEMOs for these perceived vehicles. Vehicle v_5, however, only maintains a single circular buffer for each perceived object, as each is perceived by one sensor type only. Vehicle v_1 on the other hand perceives vehicle v_2 by both CAM and Radar.

However, as for every vehicle within the simulation, there is only one GEMO within the GEM, every LEMO has to register itself as an observer to the corresponding GEMO. Whenever a GEMO is updated due to a SUMO update step, it knows about its observers and can therefore inform the corresponding LEMOs about that update. If, for example, a vehicle has been removed from the simulation, the corresponding `TraCIMobility` module is invalidated. The observation mechanism, as depicted in Figure 6.5, hence allows for the signalling about the invalidity of that particular GEMO, which results in the removal of the LEMO from every vehicle-individual LEM.

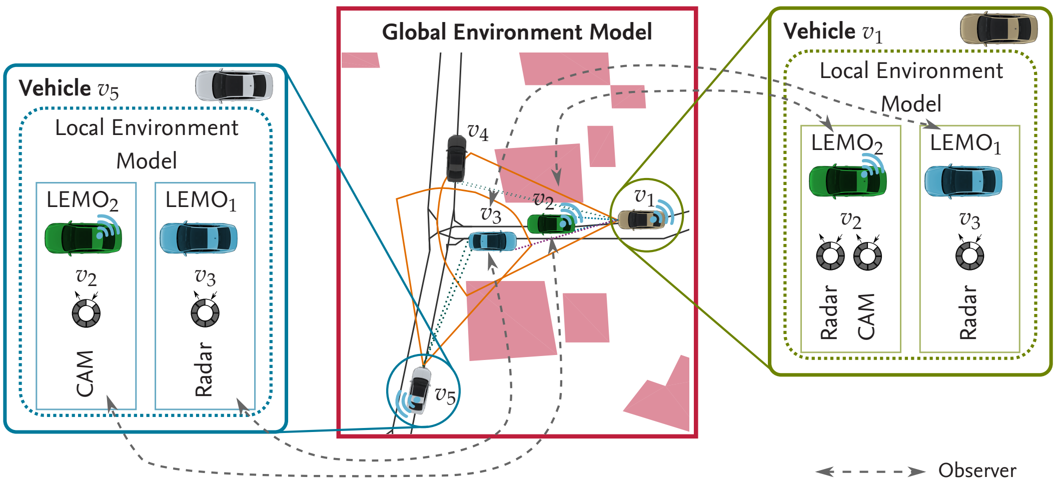


Figure 6.5.: Creation of LEMOs for observed vehicles (⁾ indicates a V2X enabled vehicle)

Every LEMO within the database exists for a limited amount of time only. The time-out for its removal from the LEM is reset, whenever it is perceived by the vehicle's local perception sensors. This mechanism allows for a temporary disturbance of a LoS (e.g. tracking of a perceived object in sharp turns) without its immediate removal from a vehicle's LEM. This behaviour is copied from sensor fusion systems in actual vehicles, in which objects no longer perceived by any sensor are maintained for a short period of time prior to being removed. Objects received by means of V2X communication are tracked for 1.1 s, taking the maximum possible time between two consecutive CAMs into account. Objects perceived by local perception sensors only are tracked for a shorter time interval of 0.2 s as measurements are performed every 100 ms by the on-board sensors. Whenever objects are perceived by multiple sensors, the LEMO is maintained for the duration of the longest valid time-out.

6.3.4. Local Perception Sensors

Local perception sensors can be created by the user simply by deriving from a parent class, which specifies the sensor interface. The interface provides virtual functions which have to be defined by the sensor according to its properties, such as the specific variables that can be measured by the sensor. A Radar sensor, for example, will return the relative velocity and distance to the observed object, whereas a camera might additionally return the relative orientation and geometric dimension of the observed object [177, 243]. When defining a set of sensors, a configuration interface is provided in order to set the range, opening angle as well as the mounting point of the sensor on the vehicle. The number of segments used for modelling the sensor's frustum, as indicated for the sensors in Figure 6.5, can also be specified. This interface may also be used for different sensor characteristics, i.e. specific shadowing effects for each sensor. Just as the services used by Artery can be specified by means of a *services.xml*-description file, local perception sensors can be associated to a vehicle by means of a separate *sensors.xml*-description file. In addition to the same filtering mechanisms as provided for Artery services, visualisation filters can be specified in order to enable different visualisation settings, e.g. for displaying LoS connections or for visualising a sensor's frustum.

As described in subsection 6.3.2, whenever a SUMO update step occurs, the GEM is updated by vehicles entering and leaving the simulation as well as by position updates of persisting vehicles. After the update procedure, an OMNeT++ signal is emitted in order to indicate updated data within the GEM. The Artery middleware of every vehicle reacts upon the emitted signal and calls the `measurement` methods of the defined sensors of the vehicle (1 in Figure 6.4). Within the `measurement` method of each sensor, the following process updates the objects within the LEM of each vehicle:

1. **Measure:** For retrieving the perceived vehicles that are located within the perception range of a sensor, the sensor configuration is passed to the GEM (2 in Figure 6.4). The GEM generates a polygon from this sensor configuration with respect to the position and orientation of the querying vehicle and checks for vehicles located

within the sensor's perception area, as detailed in subsection 6.3.2. Afterwards, the GEM returns a list of objects that may be perceived by the specific sensor (6 in Figure 6.4). Checks for obstructed LoS are also available.

2. **Complement:** The returned list of vehicles located within the sensor's perception range needs to be added to the LEM (7 in Figure 6.4). Whenever a vehicle has been sensed before, the time-out for the corresponding LEMO is reset, as detailed in subsection 6.3.3. For every object that has been measured for the first time, a new LEMO is created.

3. **Update:** The last step updates all LEMOs within the LEM. Those vehicles that have been removed from the simulation during the SUMO update step have been invalidated by means of the observation mechanisms as described in subsection 6.3.3 and therefore need to be removed from the vehicle's LEM as well. All other valid objects are updated in order to maintain the current positions and dynamic properties of the observed vehicles of the current measurement.

The task of the LEM is to store all perceived objects within the perception range of the vehicle — regardless of the sensor type. The CAM, as detailed in section 2.2.1 also contains information about a vehicle's position and dynamic state. Hence, this information may also be listed in the LEM employing the same mechanism described above. The generation of the LEMO resulting from the CAM is a task of a separately defined CAM sensor, which is also derived from the provided base-sensor interface.

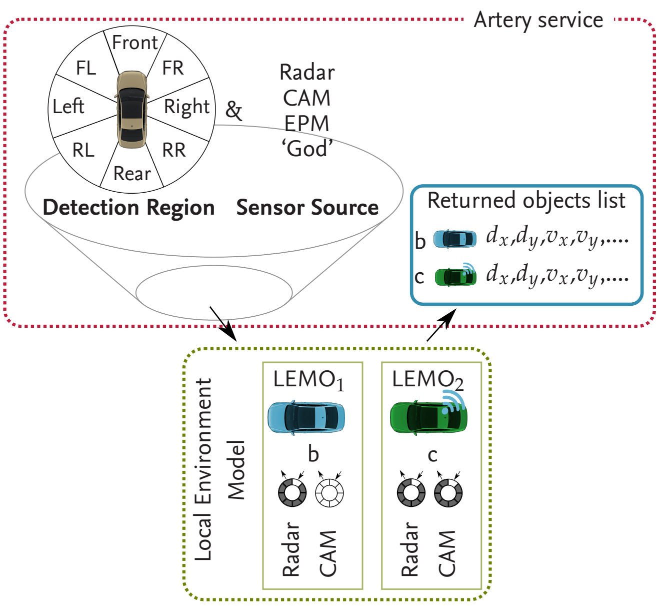


Figure 6.6.: Access mechanism of *Artery* services for the LEM. Objects are returned from the LEM according to the filter criteria.

However, if the vehicle broadcasting a CAM is additionally perceived by a local perception sensor, any data about this object has to be fused. Therefore, the proposed perception architecture also provides a low-level fusion process, as depicted in Figure 6.5. The second LEMO of vehicle v_1 in Figure 6.5, represents a fused object, as the observed vehicle transmitted a CAM and has also been perceived by a local perception sensor. As the CAM already contains all information about the originating vehicle, there is no need to link the CAM sensor to the GEM as it is the case for the local perception sensors.

6.3.5. Employing Local Perception Sensors in Vehicle Applications

For the implementation of vehicle applications, Artery services can be used as described in subsection 6.2.4. To access information about currently perceived objects from the LEM, an easy-to-use access mechanism is provided. Information can be retrieved by defining a filter, which specifies the sensor type and the region around the vehicle, from which objects from the vehicle's LEM should be returned. When providing more than one sensor type in the filter, the fused data from the corresponding sensors is returned in case multiple observations exist from several sensors. To enable for accuracy checks of the received data, a so-called 'God'-mode allows the extraction of the exact vehicle information from the LEM, as opposed to the information from the last measurement only. The specified filter is passed to an extraction method of the LEM, which is accessible by using Artery's Facilities. Figure 6.6 depicts the extraction mechanism in more detail: after providing a filter to the LEM, a list of objects fulfilling the filter criteria is returned to the Artery service.

Figure 6.7 shows screenshots of the simulation framework, including the environment model introduced in this chapter. The top-view shows the vehicles with their sensor

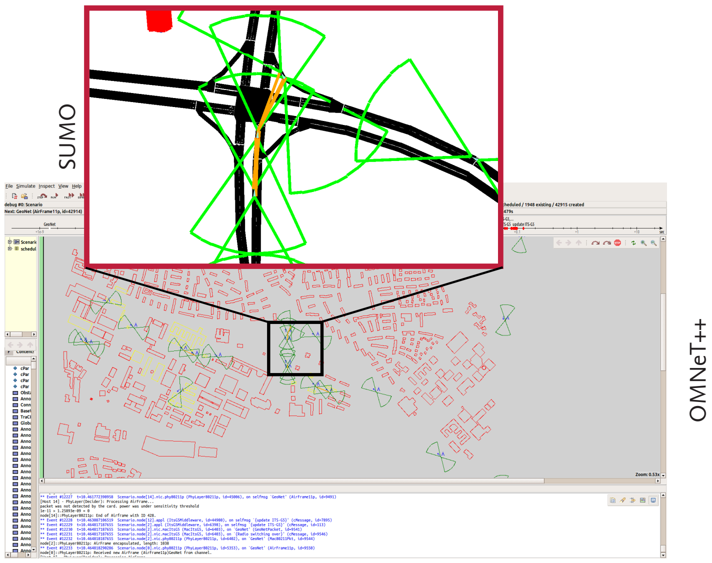


Figure 6.7.: Screenshot of local perception sensors within the simulation framework. Below: OMNeT++ screenshot. Above: corresponding scenario in SUMO with checks for LoS connections (orange lines).

frustums indicating the sensor range. Orange lines represent a valid LoS connection to the vehicles located within the sensor's perception range. The bottom view shows the respective situation within the IDE of OMNeT++.

6.4. Simulation Studies

The following sections provide the findings of two extensive simulation studies which are employed to answer the research questions regarding the macroscopic analyses defined in section 3.1. This section first introduces the parametrisation of these simulation studies, along with the corresponding performance metrics. Subsection 6.4.1 outlines the simulation parameters used for an urban environment on a smaller road network. Subsection 6.4.2 describes the setup of a second study for a larger rural environment. A description of the performance metrics is provided in subsection 6.4.3. Afterwards, section 6.5 provides the analysis regarding the potential of *Collective Perception*. The analysis of prospective network constraints due to the employed ETSI ITS G5 communication stack disrupting the working principle of *Collective Perception* is provided in section 6.6.

6.4.1. Urban Environment

The simulation study related to a scenario in an urban environment has been the first extensive study employing the Artery framework introduced in section 6.2. For reasons of comparability, the legacy map provided by the Veins framework of Erlangen, Germany has been used [203]. The corresponding road network employed within SUMO is depicted in Figure 6.8a. Demand modelling has been performed with the help of the SUMO *Traffic Modeller* [169]. Ten traffic scenarios with hotspots, directed and random traffic have been created to account for different road congestion scenarios in an urban environment. For

Table 6.1.: Simulation scenarios for the urban environment. Parameter-variations are highlighted in bold.

			Simulation (traffic) scenario									
	Parameter	**Unit**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
General	Total number of vehicles	-	303	423	43	148	230	207	224	139	184	317
	Mean travel time	s	102	134	94	104	131	119	136	120	109	97
	Map area	km^2	≈ 7.8									
	Sensor properties	-	front and rear facing sensors 80 m range, 60° opening angle									
	Traffic simulation time	s	200									
	Network simulation active	s	100–200									
ITS-G5	Radio	-	IEEE 802.11p at 5.9 GHz (CCH)									
	Data bitrate	Mbit/s	6									
	Communication range	m	300									
	Mersenne Twister seed	Integer	10									
	V2X penetration rate	%	**5, 10, 20, 40, 60, 80, 100**									

each scenario, the market penetration rate of V2X enabled vehicles has been varied between 5–100 %. To account for initialisation biases, the first 100 s of the 200 s simulation time are considered as a warm-up period to propagate vehicles into the network and are therefore not considered by the subsequent analyses. A summary of the simulation scenarios is provided in Table 6.1.

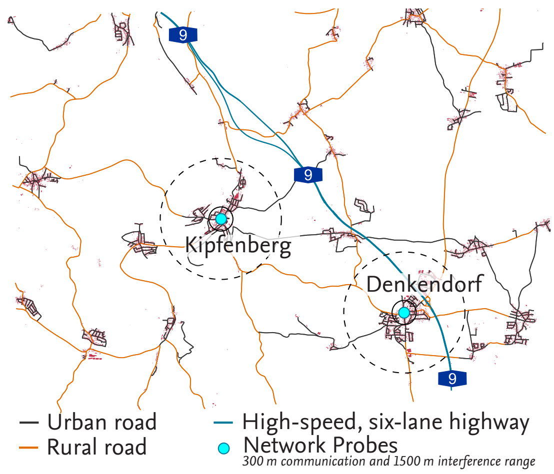
Under the assumption that future vehicles capable of V2X communication are also equipped with local perception sensors, every V2X enabled vehicle in the simulation is equipped with the same forward and backward facing Radar sensor, as detailed in Table 6.1. Non-V2X vehicles cannot communicate with these vehicles and are therefore not equipped with environment perception sensors. V2X enabled vehicles will disseminate CAMs [57] as well as an early version of the EPM. Whereas the transmission frequency for the CAMs is controlled according to the requirements defined in [57], the EPM is transmitted at a constant rate of 1 Hz. Since this setup is primarily used to determine the potential of *Collective Perception* without considering possible effects introduced by the communication stack, DCC regulations are not activated for the simulation. To correct for channel and transmission imperfections, an ideal communication range of 300 m for every V2X enabled vehicle is assumed.

The combination of ten different traffic scenarios and seven V2X market penetration rates results in 70 required simulation runs.

6.4.2. Rural Environment

The second simulation setup focused on the prospective limitations for *Collective Perception* resulting from the ITS G5 communication stack. For this purpose, a scenario with denser traffic on a highway has been selected. The simulations have been performed on a map close to the city of Ingolstadt, Germany which is characterised by a six-lane highway

(a) Road network of Erlangen, Germany



(b) Road network north of Ingolstadt, Germany

Figure 6.8.: Traffic simulator road networks

(Autobahn A9) and several towns in its vicinity, as depicted in Figure 6.8b. A summary of the employed simulation parameters is listed in Table 6.2.

Each simulation run consists of two time windows of interest, both of one minute length, whereas the latter is characterised by denser traffic. During the first time window, after about 10 min, the highway is populated with dense traffic ($\approx$ 2800 veh/h), which roughly corresponds to official measurements [140] available for the area. After about 25 min, traffic is denser in the rural areas as well, which is considered in the second time window. For evaluation of the metric outlined below, perfect communication is assumed up to a range of 300 m. Though no information exchange is possible beyond 300 m distance, all vehicles within the interference range of 1500 m compete for channel access and contribute to each other's CBR. Two fixed network probes have been placed in two small cities on the map: the probe located in Denkendorf is influenced by the dense traffic on the highway, whereas the probe in Kipfenberg records the channel load in a rather rural area only.

The study comprises six simulation flavours in which the DCC algorithms and disseminated messages have been altered. Each flavour consists of five simulation runs varying in the number of vehicles equipped with V2X communication. All V2X enabled vehicles are also equipped with a front-facing Radar sensor and are therefore enabled to share their locally perceived objects with each other.

The first set of simulations (A) represents the baseline with the maximum awareness ratio achievable in this scenario unhindered by DCC. For this purpose, the CAM and EPM are sent pairwise, i.e. one EPM for every emitted CAM. Generation of CAMs follows the rules stated in [57] and they are sent with the priority class DP2 (DCC Profile). A FoV container is added to the EPM at a beaconing frequency of 1 Hz. As a result, vehicles

Table 6.2.: Rural simulation scenario. Variations are highlighted in bold.

	Parameter	Unit	Description / Value
General	Traffic simulation time	s	1560
	Network simulation periods	s	600 – 660, 1500 – 1560
	Map area	km^2	$\approx$ 137
	Sensor properties	-	front facing Radar sensor 80 m range, 60° opening angle
	Total number of vehicles	-	1853
	Mersenne Twister Seed	Integer	10
ITS-G5	Radio	-	IEEE 802.11p at 5.9 GHz (CCH)
	Data bitrate	Mbit/s	6
	Fixed communication range	m	300
	Maximum interference range	m	1500
	DCC finite state machine		**5 $\times$ Active, Continuous Active**
	V2X penetration rate		**5 %, 10 %, 25 %, 50 %, 100 %**
	Dissemination variants		**A) CAM (DP2), EPM (unbound)** **B) CAM (DP2), EPM (DP3)** **C) Extended CAM (DP2)**

advertise their ability to share sensor data, even in traffic scenarios where no objects can be perceived. For these baseline simulations, DCC restrictions were not applied to the EPMs, i.e. they represent the worst-case scenarios in terms of the expected channel load.

Using the second parameter set (B), EPM transmissions are considered by DCC with priority DP3. For reasons of backward compatibility, this profile has been chosen for CAMs to have precedence over EPMs in cases of higher channel loads. In this setup, vehicles predating deployment of *Collective Perception* are still enabled to perceive other V2X vehicles, e.g. legacy CAMs, in situations of a high channel load, where message drops might occur.

The third parameter set (C) tries to create the lowest channel load by sending the extended CAM as introduced in subsection 5.3.2. Although the extended CAM is larger than a single CAM or EPM, it provides two benefits: channel access delay and the packet length overhead caused by lower layers occur only once.

In addition to the different message dissemination variants, two approaches of the DCC algorithms have been simulated as well. The *5x Active* Finite State Machine (FSM) corresponds to the implementation envisioned by the C2C-CC and is based on seven states, whereas the intermediate states have five different thresholds. In each state, the packet rate is regulated to control the resulting channel load [21, 64]. An alternative approach is provided by Rostami et al., where the resulting packet rate in the active state adapts linearly according to a continuous function [191].

The combination of active network simulation periods (2), different V2X market penetration rates (5), DCC implementations (2) and message dissemination variants (3) results in 60 required simulation runs.

6.4.3. Performance Metrics

The following metrics can be used for the assessment of *Collective Perception*. The first metric estimates a vehicle's current awareness, whilst the second metric is suitable for assessing DCC operations.

Awareness Ratio The metric *awareness ratio* k_s describes the sum of all actually perceived vehicles ζ_s by a sensor s with respect to all vehicles Υ within an ideal communication range. It has been introduced in [48, 108] and is defined as:

$$k_s = \frac{\sum \zeta_s}{\Upsilon}, \quad \forall \zeta_s. \tag{6.1}$$

In the post-processing of each simulation run, the awareness ratio of every V2X vehicle is determined separately for every simulation step and for every type of sensor (Radar and V2X messages). The bird's eye view of the map depicted in Figure 6.9 illustrates the methodology for a snapshot in one of the simulated scenarios. For each type of sensor, the awareness ratio is determined separately from the perspective of the host-vehicle 43. Out of 13 vehicles within the displayed ideal communication range of 300 m, the Radar-sensors of the host-vehicle detect 4 vehicles, accounting for an awareness ratio of $k_{\text{Radar}} = 0.31$. When considering the 10 vehicles perceived by CAMs only, an awareness ratio of $k_{\text{CAM}} = 0.77$ can be achieved. Due to the working principle of the environment model, any object received

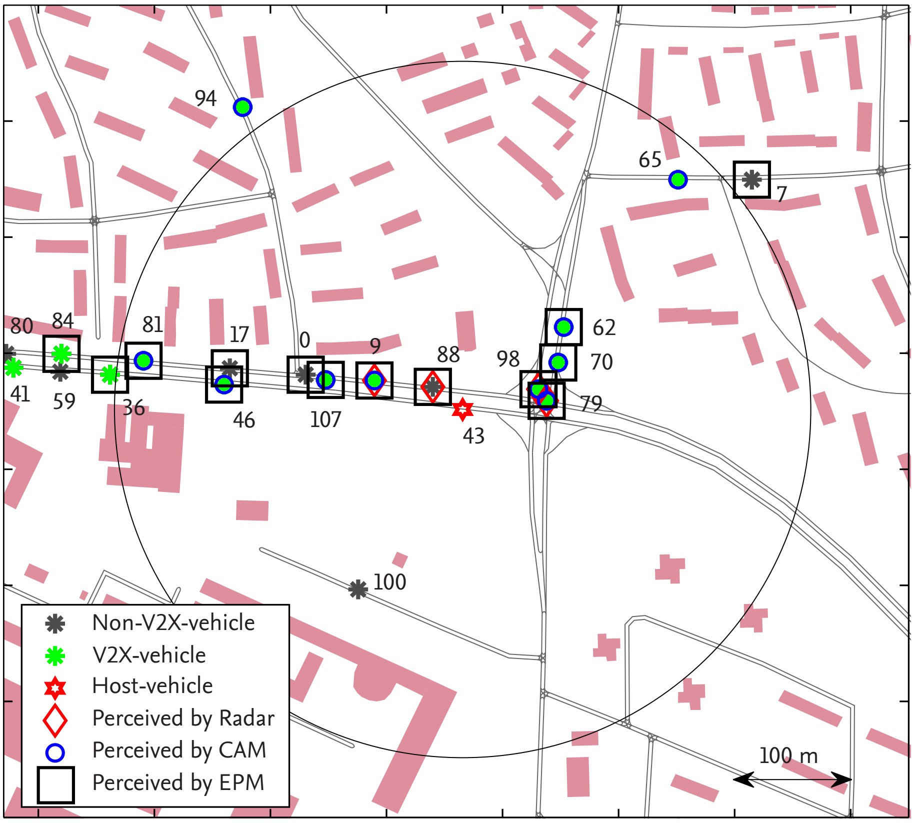


Figure 6.9.: Exemplified determination of the awareness ratio for the host-vehicle 43 in one of the performed simulations.

by V2X communication will be tracked for at least 1.1 s, as described in subsection 6.3.3. In the current snapshot, the host-vehicle is therefore still aware of vehicle 94, although located outside of the communication range.

Due to the received EPMs, the host-vehicle is aware of 14 vehicles, resulting in a specific awareness ratio of $k_{\text{EPM}} = 1.08$. An awareness ratio $k_s > 1$ demonstrates the ability of *Collective Perception* to extend the FoV of the host-vehicle beyond its communication range by the perception range of the Radar sensors of those vehicles located at the border of the communication range. As a result, vehicles 7, 36 and 84 are also known to the host-vehicle, although currently not located within its communication range (they have been published by vehicles 65 and 81 respectively, using the concept of *Collective Perception*). The host-vehicle is also aware of the non-V2X vehicles 0 and 17 within the communication range as they are broadcast by neighbouring vehicles. The combined awareness ratio for all sensors yields $k_{\text{All}} = 1.23$. However, the metric does not indicate that the host-vehicle is in fact not aware of all vehicles within its communication range: as there is no V2X enabled vehicle within the vicinity of the non-V2X enabled vehicle 100, the host-vehicle cannot be aware of this object.

Channel Busy Ratio Whilst the awareness ratio is a suitable metric for describing the completeness of a vehicle's current environment model, it is not suitable for examining the characteristics of a VANET. For this purpose, a more network-oriented metric is the so-called Channel Busy Ratio (CBR), specifically aiming at describing the current utilisation of the communication channel. The metric is determined by assessing the channel over a period of 100 ms on the access-layer through the network interface card. Given the duration of one OFDM symbol of 8 µs [59] (48 bit per symbol at a data-rate of 6 Mbit/s in the G5-CCH), the channel is assessed for $|N| = 12{,}500$ symbols in order to determine the measured Channel Busy Ratio CBR_m. Whenever the received signal strength exceeds −85 dBm, the channel is assessed as *busy* for this symbol [25]. The *local* channel utilisation over the previous sampling period is then calculated within the *CBR evaluation* component of the management layer as:

$$CBR_m = \frac{|N_{busy}|}{|N|}, N_{busy} \subseteq N. \tag{6.2}$$

The C2C-CC's Basic System Profile (BSP) [21] demands exponential smoothing of the metric to account for oscillations. The smoothed channel load CBR_t is calculated as:

$$CBR_t = \alpha * CBR_m + \beta * CBR_{t-1}, \alpha = \beta = 0.5. \tag{6.3}$$

As such, CBR_t can be used to compare the resulting channel load of different parameter settings. However, as the nodes travel through the road network whilst determining the channel load, comparisons between different runs would only be possible for the same node. Consequently, two passive static network probes have been installed in the rural scenario as described in subsection 6.4.2.

6.5. The Potential of Collective Perception

The focus of the first simulation study presented in subsection 6.4.1 was the analysis of the potential of *Collective Perception* on different levels of detail. As stated above, an early version of the proposed EPM format presented in subsection 5.3.1 has been used for sharing sensor data with other vehicles. The findings of the study influenced the further development of the derived data containers presented in section 5.3. Although focussing on analysing the constraints due to the ITS G5 communication stack, the second simulation study presented in subsection 6.4.2 also provides an analysis regarding achievable awareness ratios in an urban and a highway scenario. The findings of the second study further influenced the proposed message formats, as different mechanisms for accommodating the required data containers with the objective of reducing the network load have been identified.

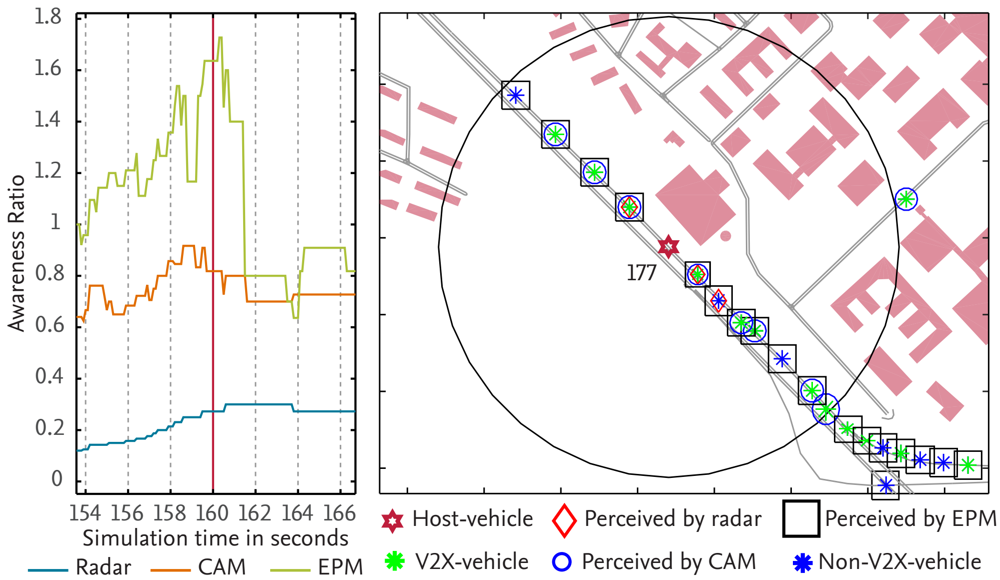
The following subsections provide the findings of these studies on different levels of detail. Subsection 6.5.1 aggregates the potential on a scenario level. Subsection 6.5.2 then provides the next aggregation step, in which the findings of multiple simulations are combined.

6.5.1. Time Variation Analysis

The first step of the post-simulation analysis determines the achievable awareness ratio specific to different data sources, as outlined in subsection 6.4.3. The result of this process is a time-variant vector for every vehicle within the simulation, containing the corresponding awareness ratios specific to each data source.

Awareness ratio for a single vehicle

Figure 6.10 outlines the mechanisms for determining the sensor specific awareness ratio in more detail. The Figure depicts the calculated awareness ratio for the exemplary vehicle 177, along with the current driving environment at a simulation time of 160 s. As shown in Figure 6.10a, the sensor specific awareness may vary significantly with respect to the current distribution of vehicles. In combination with Figure 6.10b, the drop in the awareness ratio due to the EPM k_{EPM} at around 161 s can be explained. The depicted map shows the distribution of vehicles located around the host-vehicle 177 at a simulation time of 160 s. As for any V2X vehicle in the urban scenario simulations, the host vehicle is equipped with a front- and rear-facing Radar sensor. As a result, 3 out of 11 vehicles within the relevant communication range are perceived by means of the Radar sensor, yielding $k_{\text{Radar}} = 0.27$. The awareness ratio due to received CAMs yields $k_{\text{CAM}} = 0.82$ (9 out of 11 vehicles). However, the awareness ratio due to the EPM yields $k_{\text{EPM}} = 1.64$ (18 out of 11 vehicles). The resulting awareness ratios are influenced by two effects: the virtual extension of the perception range as well as the tracking duration in a vehicle's LEM. For



(a) Awareness ratio over time (b) Current scenario at simulation time 160 s

Figure 6.10.: Awareness ratio analysis for vehicle 177 for urban simulation scenario 2 at 60 % V2X market penetration rate

the first effect, the host-vehicle's current perception range is extended by the range of these V2X vehicle's Radar sensors located just at the border of the communication range of 300 m. As a result, 8 vehicles outside of the current communication range are known to the host-vehicle due to *Collective Perception*. For the second effect, the tracking duration of the vehicle's environment model for each object is the reason for the single vehicle received via CAM in the east of the host-vehicle's current position. Both effects may contribute to an over-estimation of the benefit of a sensor technology. The sudden drop in the resulting awareness ratio due to the EPM at around 161 seconds can hence be explained to held-off EPMs from the vehicle currently located at the border of the communication range. The effect of the virtually extended perception range ceases to apply, when the V2X vehicles leave the current communication range.

However, first insights to the potential of *Collective Perception* may already be provided: Although only 60 % of the vehicles in this exemplary scenario are equipped with V2X communication, the overall awareness of the host-vehicle k_{All} yields 1.82. Without *Collective Perception*, this ratio is reduced to $k_{\text{Radar + CAM}} = 0.91$ in the current scenario, when combining vehicles perceived by CAMs and Radar sensors only.

Aggregated awareness ratio for all vehicles in the same scenario

The second step of the analysis consists of aggregating the awareness ratios specific to each equipped vehicle over the entire simulation period. Figure 6.11 depicts the result of this

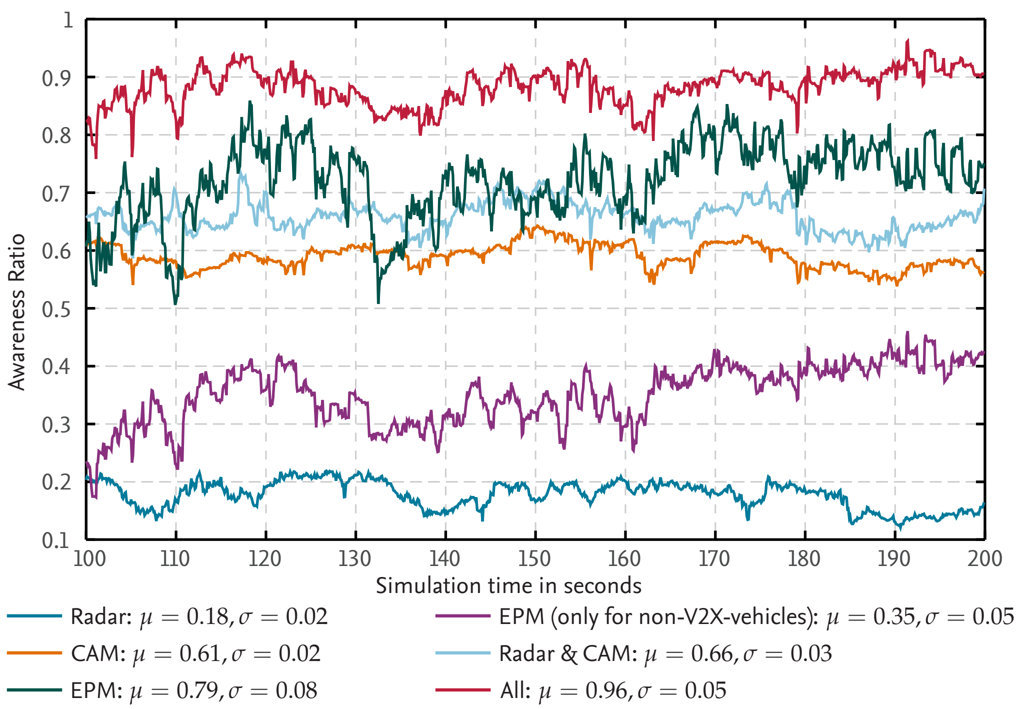


Figure 6.11.: Aggregated time variation of the awareness ratio metric for the urban simulation scenario 2 at 60 % V2X market penetration rate over all V2X equipped vehicles

aggregation for the same scenario described above, albeit each data-point corresponds to averaged vehicle specific awareness ratio values. Whilst for the vehicle-specific analysis, the resulting awareness ratio depends on the current driving environment, the aggregation over all vehicles levels local phenomena. The depicted aggregation is taken from a scenario with a V2X market penetration rate of 60 %. As a consequence, the average awareness ratio due to received CAMs yields about $k_{\mathrm{CAM}} = 0.61$. Similarly, the awareness ratio resulting from Radar measurements yields about $k_{\mathrm{Radar}} = 0.18$. When combining these two sensor types, taking only unique perceived vehicles into account, an average awareness ratio of $k_{\mathrm{Radar+CAM}} = 0.66$ is reached. This effect shows that although in certain scenarios, local sensors may have a dramatic impact for increasing a vehicle's local awareness, the average contribution to the overall awareness ratio due to local sensors in this setup is comparatively small.

Adding *Collective Perception* to the picture, a dramatic increase in the number of detected objects within a vehicle's communication range, especially at low market penetration rates, is observed. The average awareness ratio solely due to EPMs in the presented scenario is about $k_{\mathrm{EPM}} = 0.79$. Combining all three sensor types, an overall average awareness of $k_{\mathrm{All}} = 0.96$ may be reached — although on average only 60 % of the surrounding vehicles are equipped with V2X communication capabilities. As described in section 5.2.3, EPMs are transmitted by V2X vehicles for any object perceived by local perception sensors — regardless of the vehicles' communication capabilities. To demonstrate the average number of vehicles only perceived by local perception sensors, the purple curve indicates that about 35 % of the vehicles transmitted by EPMs are non-V2X vehicles. However, transmitting only non-V2X vehicles as part of the EPM diminishes the effect of extending a vehicle's perception range by the sensor range of those vehicles located at the border of the current communication range, as described above. This might hinder certain ADAS applications, such as a vehicle-out-of-sight warning, in situations where communication range is limited, e.g. due to obstacle shadowing. Consequently, objects included in any type of *Collective Perception* message should not be differentiated by their ability to communicate.

Distribution of time variant standard deviations

Taking the corresponding standard deviations for each sensor type into account, it is apparent that EPMs exhibit the largest variation. This observation is due to the particular dependency of *Collective Perception* on the current driving scenario. Up to a certain extent, this holds true for most sensor types, especially in dense traffic situations in the vicinity of a specific vehicle, where most of the surrounding vehicles may be perceived by local sensors or where the likelihood of encountering another V2X-enabled vehicle is comparatively high. As a result, the utility of *Collective Perception* decreases in these situations. Additionally, in situations where only a few vehicles are located within another vehicle's local sensor range, *Collective Perception* has a smaller impact. To provide an overview of the resulting variations, Figure 6.12 depicts the distribution of occurring standard deviations for the different traffic scenarios in the urban environment for different V2X market penetration rates. It can be observed that the variations in resulting awareness ratios due to CAMs is almost

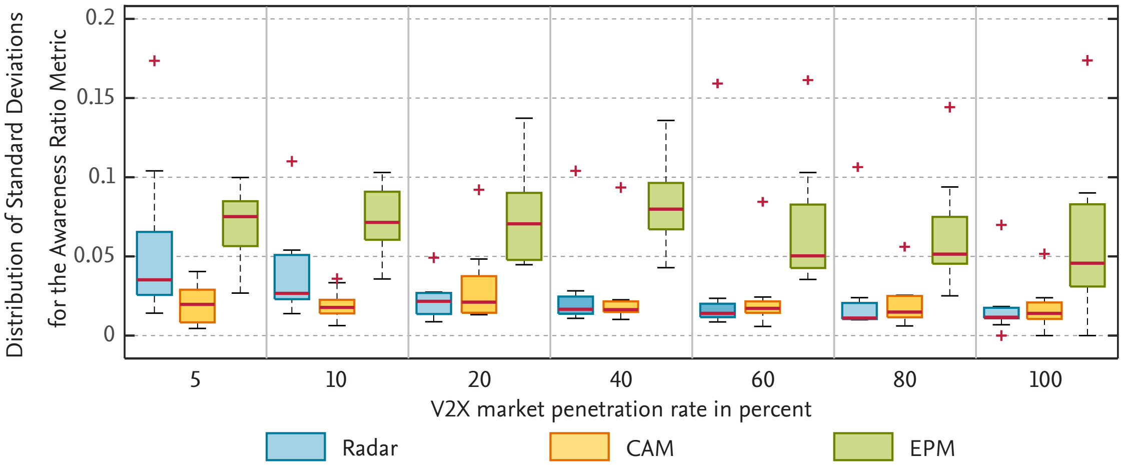


Figure 6.12.: Distribution of time variant standard deviations of sensor specific awareness ratios for the urban scenario. Each Boxplot summarises ten different traffic scenarios.

constant at a level around $k_{\text{CAM}} = 0.02$. With increasing market shares of V2X vehicles, and therefore vehicles equipped with Radar sensors, the variations in the resulting awareness ratios due to the Radar stabilise at around $k_{\text{Radar}} = 0.018$. The large variation at 5 % market share is due to the validations which highly depend on the current driving scenario, where some vehicles equipped with sensors may either be scattered around the city, or clustered at an intersection. The largest variations, however, occur for the awareness ratio due to EPMs for all market shares. As outlined above, this is for one part due to the extended perception range because of vehicles located at the border of the current communication range. For the other part, these variations depend on the current traffic situation: in every scenario, some isolated vehicles may well be within communication range of other V2X vehicles, but may not perceive any other vehicles with their local sensors. Consequently, this contributes to the stabilisation of the variation for the corresponding awareness ratio due to CAMs, whilst increasing variations for the effectiveness of *Collective Perception*.

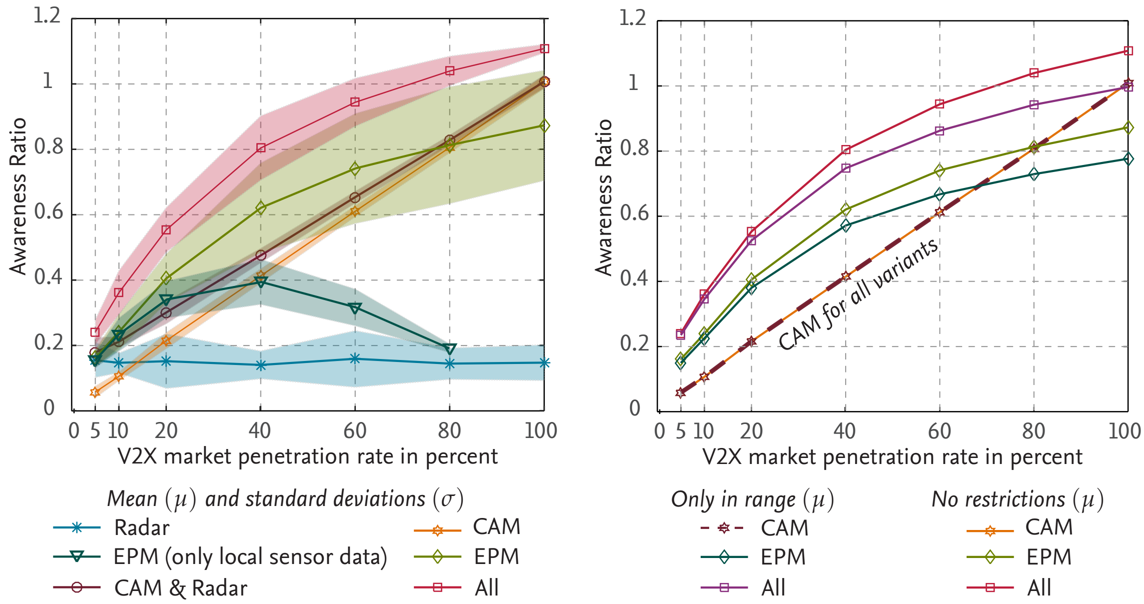
6.5.2. Aggregated Potential Analysis

Most of the following explanations in this section have been partially taken or adapted from [108].

The analysis presented in subsection 6.5.1 focuses on presenting the potential of *Collective Perception* for specific scenarios. However, the overall potential becomes apparent, when aggregating over all simulation scenarios.

Aggregated Analysis

Figure 6.13a depicts the corresponding sensor specific awareness ratios, aggregated over all ten traffic scenarios for the urban environment. The average awareness ratio for each vehicle resulting only from Radar sensors is almost constant, regardless of the penetration rate. This is due to the properties of the sensors as well as to the scale basis of 300 m for the metric. The variation of the standard deviation results from the dependency on the current



(a) Awareness ratio with standard deviations for every sensor type

(b) Virtual extension of perception range

Figure 6.13.: Aggregated awareness ratio diagrams for the urban environment (first simulation study)

traffic scenario: the Radar sensors of vehicles located close to a populated intersection are likely to perceive more objects than vehicles located on residential roads.

As expected, the awareness ratio due to CAMs is directly proportional to the V2X market penetration rate of the corresponding scenario. It is important to note that when combining local Radar and CAM data, the awareness ratio increases with diminishing marginal gain: with increasing V2X market penetration rate, the vehicles perceived by Radar are more likely to be equipped with V2X communication. As a result, the contribution of the Radar sensor to the vehicle's combined (CAM & Radar) awareness ratio decreases.

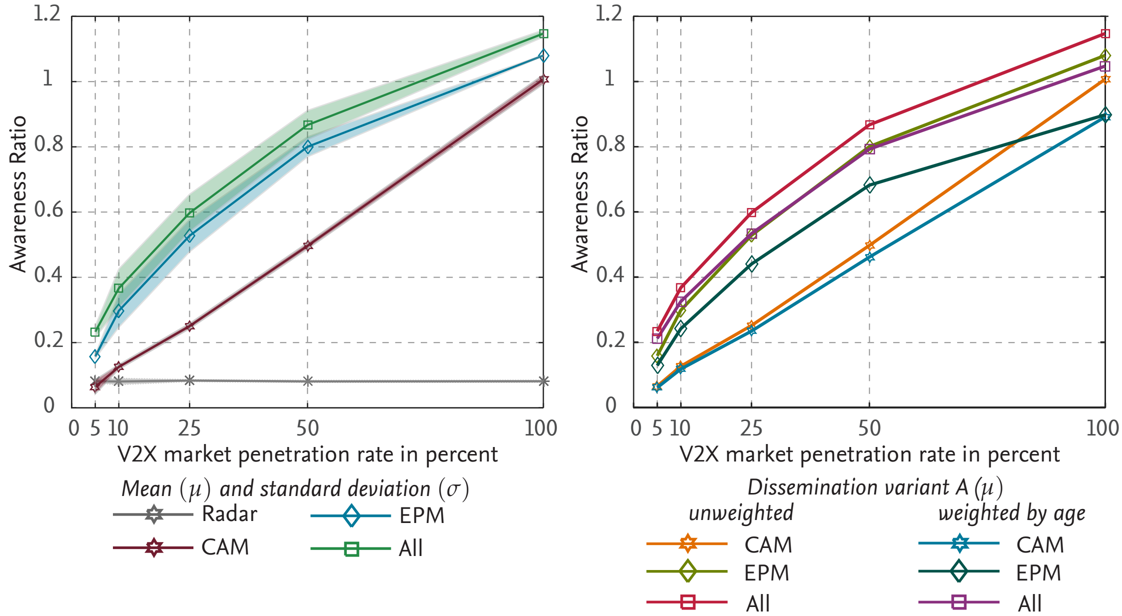
The broadcasting of locally perceived sensor objects in the network by means of disseminating EPMs has a significant effect on all scenarios. Especially in situations of low penetration rates, the concept of *Collective Perception* unveils a significant leverage. To pick an example, at a V2X market penetration rate of 20 %, the resulting combined awareness ratio due to Radar and CAM yields about $k_{\text{Radar + CAM}} = 0.3$. With the addition of EPMs, the combined awareness ratio increases to $k_{\text{All}} = 0.54$. Hence, *Collective Perception* almost doubles the average number of perceived vehicles, especially at lower market penetrations. The more vehicles are equipped with V2X communication, the more traffic situations are covered by the analysis. As a consequence, the corresponding variation in the effect of *Collective Perception* increases. At the same time, the increasing market share helps to counteract this effect, as an increasing number of vehicles are able to broadcast their positions themselves, which decreases the corresponding standard deviations of the overall awareness ratio.

The displayed dark-green line in Figure 6.13a describes the effect, when rebroadcasting only non-V2X enabled objects. This helps answering the question of which objects should be transmitted as part of an EPM: in case only unequipped vehicles are considered for transmission, the number of potential vehicles to be transmitted as part of an EPM decreases with increasing V2X market penetration rate. However, when rebroadcasting all local sensor objects regardless of their V2X capabilities, the awareness ratio can be increased even further, as the probability of receiving information about objects outside of the communication range increases. This finding becomes even more relevant, considering the fixed communication range of 300 m used for these simulations. When accounting for more realistic and diverse communication ranges, for example in urban scenarios where buildings and other obstacles decrease the communication range significantly, *Collective Perception* can counteract these limitations. In intersection scenarios, for example, vehicles located in one arm of an intersection might be out of another vehicle's communication range. With the help of *Collective Perception*, other vehicles with a current LoS into that particular arm of the intersection, may still transmit information about those other vehicles not located within the communication range. Consequently, unless message size or communication channel restrictions demand for sparse resource utilisation, objects detected by local perception sensors which are themselves V2X-enabled should be included in a prospective message format for *Collective Perception*.

Effect of virtually extended perception range

Subsection 6.5.1 outlines the effect of a virtual extension of a vehicle's perception range due to those vehicles located at the border of the current communication range. To quantify this effect, Figure 6.13b depicts the equivalent analysis of resulting awareness ratios, when only considering those vehicles located within the communication range. The combination of all sensor types for the determination of the vehicle's awareness ratio shows that considering all vehicles — regardless of their presence within the communication range — results in an awareness ratio exceeding 100 %. The difference compared to the analysis, when only vehicles located within the communication range are considered, yields about 11 % at a V2X market penetration rate of 100 %. The likelihood of V2X vehicles located at the border of the communication range decreases with diminishing V2X market penetration rates. It should be noticed that this effect is mainly due to shared sensor data as the corresponding awareness ratio plots for CAMs are identical. Naturally, this is the expected behaviour, as CAMs disseminated by vehicles located outside of the communication range cannot be received. Consequently, even if all vehicles are equipped with V2X communication, *Collective Perception* is still able to provide an increase in a vehicle's awareness.

So far, only the urban simulation scenarios have been analysed. As expected, the findings for the larger rural scenario do not differ significantly, as depicted in Figure 6.14a. The diagram shows the corresponding aggregated potential analysis of *Collective Perception* for the rural scenario for message dissemination variant A (see Table 6.2), in which CAMs have



(a) Awareness ratio with standard deviations (Dissemination variant A (EPM unbound))

(b) Awareness ratio weighted by data age

Figure 6.14.: Aggregated awareness ratio diagrams for the rural environment (second simulation study)

been transmitted along with the EPMs. Whereas for the latter, DCC is active and CAMs are disseminated with DCC-profile 2, EPMs are transmitted whenever a CAM is generated without DCC restrictions. The awareness ratio resulting from the Radar sensor yields about $k_{\text{Radar}} = 0.09$ (compared to about $k_{\text{Radar}} = 0.18$ in the urban scenarios), as the vehicles are only equipped with a front-facing Radar sensor. Furthermore, the standard deviations of the corresponding awareness ratios of both Radar and CAM are lower compared to the urban scenario, as most of the vehicles are located on the highway with dense traffic and are therefore exposed to homogeneous traffic situations compared to an urban environment. However, the overall awareness ratio, when combining all data sources is very similar to the urban scenario. As previously identified, *Collective Perception* exhibits its largest potential especially at low V2X market penetration rates.

Effect of object age

As mentioned in subsection 6.5.1, next to a virtual extension of a vehicle's perception range due to other communicating vehicles located at the border of the communication range, the effect of tracking objects in the vehicle's environment model on the corresponding awareness ratio needs to be analysed. Subsection 6.3.3 introduced the concept of different horizons of prediction for perceived objects with respect to their sensor source, i.e. objects perceived by any message received via V2X are tracked for at least 1.1 s until removed from the LEM in case no more updates arrive for that particular object. Consequently, the LEM may still maintain an object, although no longer within the current (virtual) perception range. The impact of this effect can be estimated by weighting each object in the LEM according to its age. This process takes into account that the older an object in the LEM, the longer the prediction duration and hence the higher the associated inaccuracies of the object's state variables. As a result, the weighted awareness ratio k_s^w considers the current age $t_{\zeta_i}^{\mathrm{age}}$ of the perceived object ζ_i for every type of sensor s. The influence of each vehicle in the LEM on the corresponding awareness ratio is scaled with respect to its current age. The scaling factor $a_{\zeta_i}^{\mathrm{s}}$ is determined by assessing the last time of update $t_{\zeta_i}^{\mathrm{update}}$ with respect to the current time t^{now} in relation to the tracking interval t_s^{track} specific for each data source s, e.g. 1.1 s for any object received via V2X communication. It should be noted that $t_{\zeta_i}^{\mathrm{update}}$ does not correspond to the reception time of the message but to the encapsulated generation delta time, to account for measurement and processing delays:

$$a_{\zeta_i}^{\mathrm{s}} = 1 - \frac{t_{\zeta_i}^{\mathrm{age}}}{t_s^{\mathrm{track}}} = 1 - \frac{t^{\mathrm{now}} - t_{\zeta_i}^{\mathrm{update}}}{t_s^{\mathrm{track}}}. \tag{6.4}$$

In the next step, when calculating the corresponding awareness ratio for each data source as outlined in equation 6.1, rather than determining the number of vehicles in the LEM with respect to those vehicles located within communication range, the sum of the scaling factors is considered:

$$k_s^w = \frac{\sum a_{\zeta_i}^{\mathrm{s}}}{Y}, \quad \forall \zeta_i. \tag{6.5}$$

Figure 6.14b shows both the unweighted along with the weighted awareness ratio diagrams. For all depicted data sources, the data age of the vehicles in the LEM has a considerable effect on the resulting awareness ratio. Generally, it can be observed that with increasing V2X market penetration rate, the effect of ageing objects increases: the higher the market share, the higher the channel load. In return, DCC regulations reduce the packet transmission frequency of the nodes, causing an increased data age of objects in a vehicle's LEM. This effect is noticeable for both awareness ratios due to CAMs and EPMs. As a consequence, the combined weighted awareness ratio is reduced by up to 10 % at a V2X market share of 100 % compared to the unweighted case due to data age.

6.6. Collective Perception and ITS G5

Most of the following explanations in this section have been partially taken or adapted from [104].

Section 6.5 demonstrates the effectiveness of *Collective Perception* in a vehicular ad-hoc network. However, the presented analysis did not consider external effects of the employed protocol stack possibly hindering the realisation of *Collective Perception*. Nevertheless, the simulations of the potential analysis already considered a complete ETSI ITS G5 communication stack for every communication enabled vehicle. For the additional EPM to be transmitted, however, DCC mechanisms had been disabled. Consequently, the performed simulations for the analysis of the potential of *Collective Perception* merely demonstrate the general capability of the ITS G5 stack to enable sharing of sensor data.

Therefore, the following subsections discuss the influence of DCC mechanisms on the effectiveness of *Collective Perception*. For this purpose, the simulations performed in the rural environment and outlined in section 6.4.2 provide different message dissemination variants: Variant A performs baseline simulations with DCC deactivated for EPM transmission. Variant B then activates DCC for EPMs. For variant C, rather than transmitting a second message, the legacy CAM is extended by those containers required for *Collective Perception*, as described in subsection 5.3.2. Subsection 6.6.1 takes the aggregated potential analysis as the basis for identifying the influence of DCC regulations on the resulting awareness ratios. An in-depth analysis of corresponding channel load measurements is given in subsection 6.6.2.

6.6.1. Effect of DCC on Awareness Ratio

Figure 6.15 depicts the resulting average awareness ratios with respect to the message types for different market penetration rates and dissemination variants. Every depicted data-point is the result of calculating the awareness ratio with respect to the sensor type (e.g. Radar, CAM and EPM) for every equipped vehicle at any point in time, averaged over both network simulation periods. The dotted grey line depicts the average awareness ratio resulting from Radar sensors, which is unaffected by V2X market penetration rates. Regardless of the dissemination variant, the average awareness ratio due to the CAM alone is almost identical for all market penetration rates. Hence, DCC regulations have no effect on the performance of CAM transmissions.

The awareness ratio resulting from the EPM alone, however, paints a different picture: at a market penetration rate of 100 %, the extended CAM and EPM (unbound) dissemination variants both achieve an awareness ratio higher $k_{\text{EPM}} > 1$. As identified above, this is the result of other vehicles located just within the communication range being able to perceive vehicles by Radar outside of the communication range of the host-vehicle. There is also almost no difference in the resulting awareness ratio between the extended CAM and EPM (unbound) variant.

When considering the same scenario with DCC activated for EPM transmission, this image changes dramatically: the EPM (DP3) case yields a considerably lower awareness ratio throughout all V2X market penetration rates. Even worse, in the case of 100 % equipped vehicles, where an awareness ratio of more than 1 shall be obtainable by means of *Collective Perception*, the value drops even below the ratio obtained in the case of 50 % equipped vehicles. The overall awareness ratio confirms this observation: a dramatic gain in awareness can be achieved with extended CAM and EPM (unbound) compared to the CAM-only case, e.g. 35 % of the relevant vehicles are known to the host-vehicle although only 10 % were equipped with V2X communication. In the case of EPM with DP3, however, an overall combined awareness ratio of only about 29 % is reached (red line in Figure 6.15). At higher market penetration rates, the effect of *Collective Perception* on the overall awareness ratio is reduced, which marginally reduces the aggregated awareness.

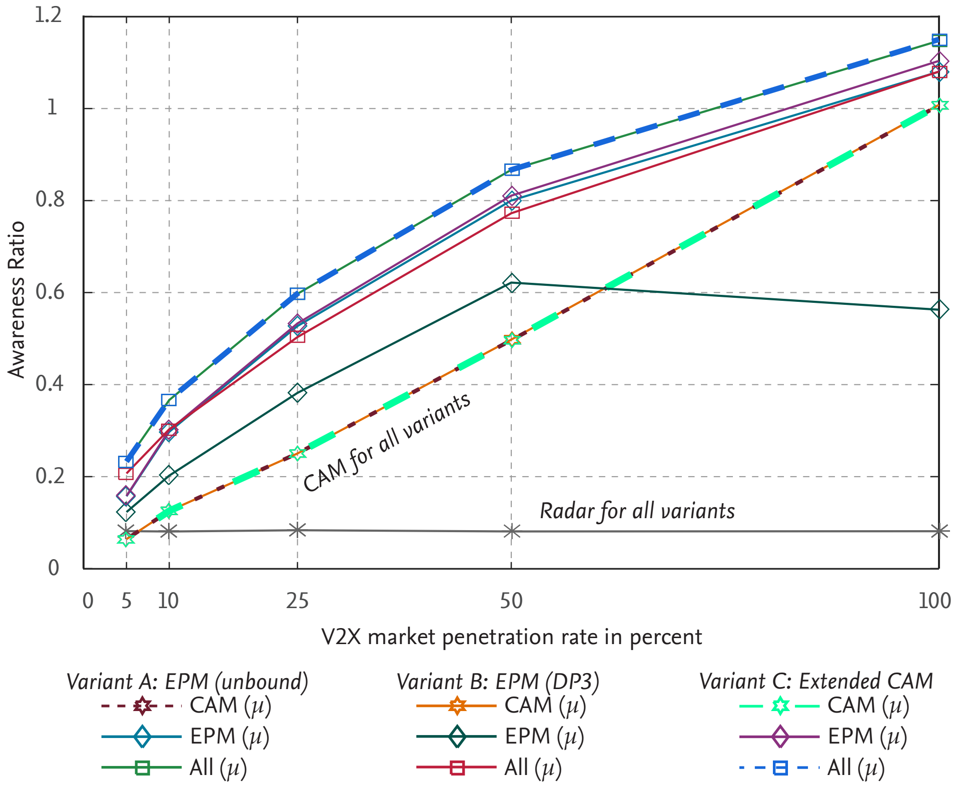


Figure 6.15.: Effect of 5x active state DCC FSM on resulting awareness ratio

Hence, the following conclusion can be drawn: the performed simulations of message dissemination variants A and C demonstrate that although DCC is activated for CAM transmissions, the ITS G5 protocol stack is capable of additionally transmitting a second (larger) message for *Collective Perception*. However, when activating DCC for EPM transmissions, a significant amount of EPMs is not transmitted at all. Taking the other dissemination variants into perspective, it seems as if this extent of message drops is not required. These drops are caused by an increased channel load, which causes DCC to regulate packet transmission frequencies. However, not considering header overhead for two messages sent on the same channel, the extended CAM variant C is capable of achieving the same awareness ratio as in variant B, despite of activated DCC operations. Therefore, DCC adaptations might be required to be able to transmit a message for *Collective Perception* on the CCH along with the CAM. Above all, this finding holds true for any other message that is supposed to be transmitted on the CCH along with the legacy DENM and CAM formats.

6.6.2. Channel Busy Ratio Analysis

The necessity for DCC-adaptations can be explained by taking the resulting CBR measurements with respect to the dissemination variants into account, as depicted in Figure 6.16. The displayed channel load measurements originate from the network probe in Denkendorf, which is subjected to high network loads due to the highway located within its

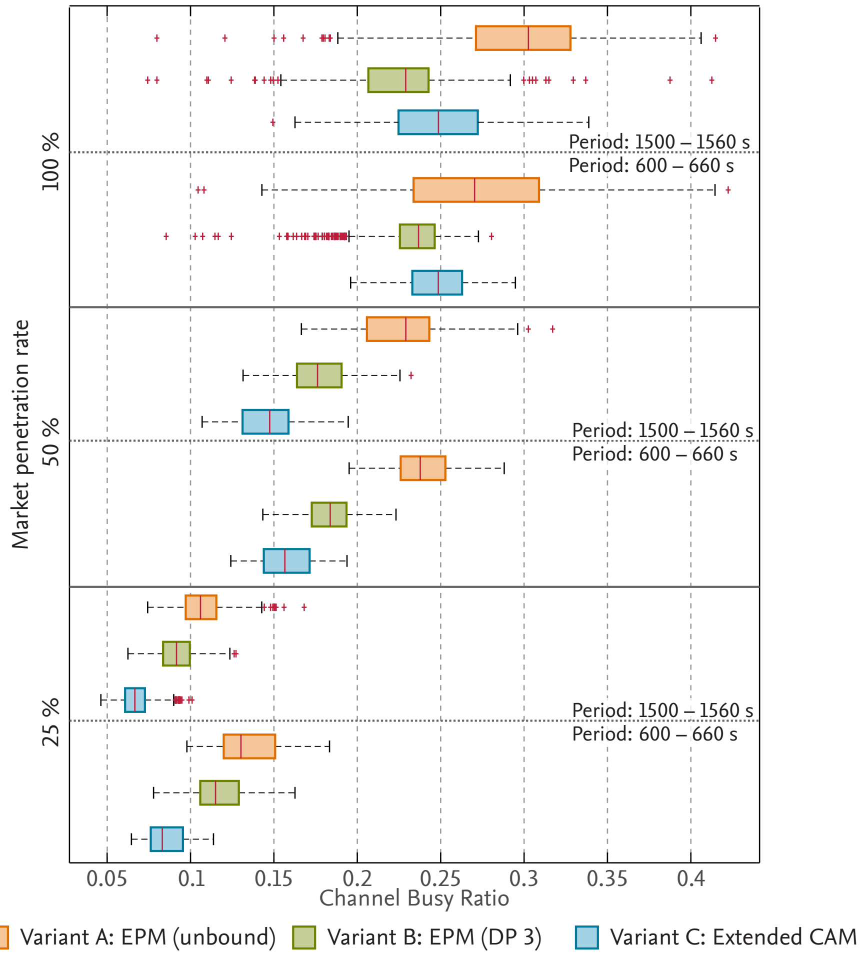


Figure 6.16.: Channel Busy Ratio for different market penetration rates and dissemination variants for the probe intercepting highway traffic

interference range. In addition to CBR measurements, Table 6.3 lists the corresponding average number of vehicles located within the probes' interference ranges. It can be observed that throughout all market penetration rates, variant A (EPM (unbound)) exhibits the highest channel load and the largest variance. In addition, except from the 100 % scenario, variant C (extended CAM) exhibits the smallest average channel load footprint and lowest variance, which is due to the smallest packet overhead out of all three dissemination variants.

The significant drop in the awareness ratio of the EPM sent with DP3 in the case of 100 % penetration rate as depicted in Figure 6.15, however, is tied to DCC behaviour: with increasing penetration rates, the channel becomes progressively congested as more vehicles compete for the same share of channel capacity. In order to keep overall CBR within limits, DCC elongates intervals between transmissions. At some point, these intervals are too long for transmitting both CAMs and EPMs, until generation of the follow-up CAM. Consequently, EPMs are enqueued by DCC and only dequeued if no CAM with higher

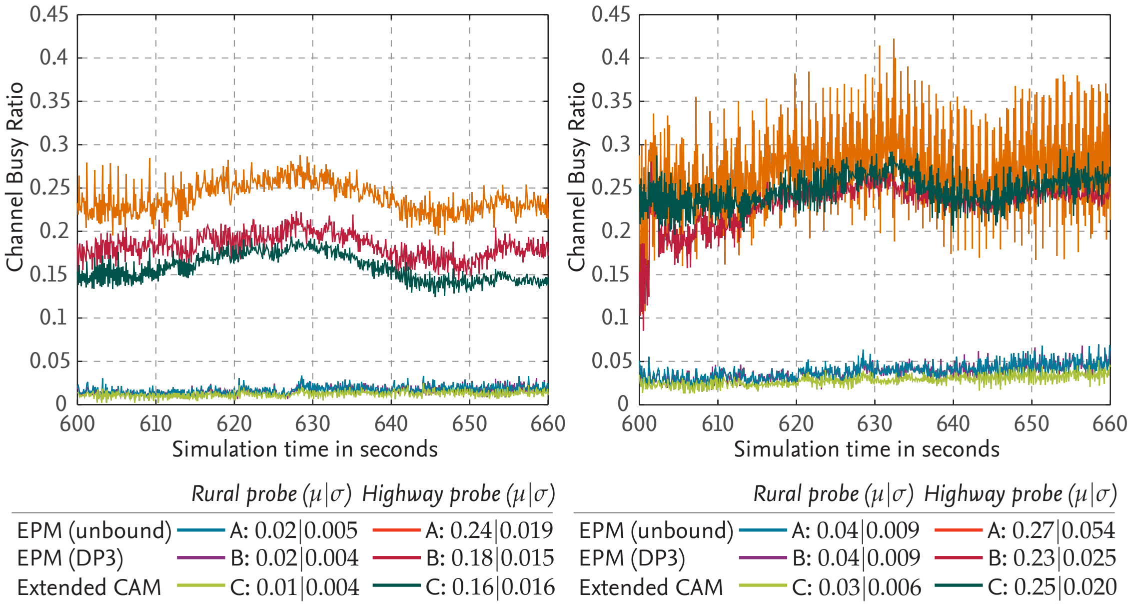
Table 6.3.: Number of V2X vehicles in interference range of network probes

	Time (s)	Penetration Rate (%)	Number of Vehicles in Interference Range ($\mu \pm \sigma$)
Probe with highway traffic	600–660	5	5.8 ± 1.0
		10	17.8 ± 2.0
		25	37.5 ± 4.1
		50	70.9 ± 5.4
		100	128.8 ± 5.3
	1500–1560	5	6.9 ± 1.0
		10	17.1 ± 1.4
		25	33.5 ± 2.4
		50	71.9 ± 3.1
		100	161.1 ± 3.0
Probe with rural traffic	600–660	5	1.7 ± 0.5
		10	2.8 ± 0.6
		25	4.8 ± 0.7
		50	10.8 ± 1.4
		100	29.2 ± 4.7
	1500–1560	5	4.0 ± 0.5
		10	9.9 ± 0.6
		25	22.8 ± 1.1
		50	47.8 ± 1.8
		100	87.7 ± 2.3

priority (DP2) has to be sent at the next transmission opportunity. As a result of this DCC intervention, the average awareness ratio due to *Collective Perception* drops below 60 % at a V2X market penetration rate of 100 %, i.e. more than 40 % of EPMs are suppressed by DCC operation. This effectively reduces the channel load and consequently, variant B (EPM (DP3)) exhibits in fact the smallest average CBR in this case.

CBR measurements, however, do not suggest the necessity of this strict behaviour: whilst both other variants convey more information, CBR measurements shown in Figure 6.16 never exceed 50 % in any case, i.e. DCC causes an under-utilisation of available resources for variant B.

Since the boxplots of Figure 6.16 show considerable CBR variance for higher penetration rates, it is promising to investigate CBR measurements over time for these cases. Figure 6.17 depicts CBR measurements of both network probes during the first simulated time window ranging from 600–660 s. The dense traffic on the nearby highway has a profound impact on the channel load, as the probe subjected to highway traffic exceeds the measurements of the other probe by far. Low frequency oscillations, which are especially noticeable at the probe subjected to rural traffic, can be attributed to the vehicle traffic changing slowly during the simulation period.



(a) 50 % V2X market penetration rate **(b)** 100 % V2X market penetration rate

Figure 6.17.: Channel Busy Ratio diagrams of passive network probes for different V2X market penetration rates in the rural scenario

Figure 6.17a depicts the measured CBR for a market penetration rate of 50 %. As discussed for Figure 6.16, variant C (extended CAM) exhibits the lowest average channel load. Besides the highest CBR measurements, variant A (EPM (unbound)) also accounts for the highest variations. These can be attributed to the fact that the second message (EPM) is transmitted unsolicited just after each CAM, i.e. DCC regulations come into effect with some delay. Although variant B comprises two individual messages just as for variant A, EPMs are dropped more frequently at the cost of a significantly lower awareness ratio. This can be observed by the constantly lower CBR of variant B, despite the same number, length and time of message creation for both variants.

Taking Figure 6.17b into account, the effect described above is even more prominent. The variance in the CBR measurements for the EPM (unbound) variant increases even further, as twice as many messages are created for transmission. For variant B (EPM (DP3)), DCC restricts the transmission of the EPMs in favour of a lower channel load comparable to variant C (extended CAM) — but at the cost of a significantly decreased awareness ratio. At the probe subjected to rural traffic only, DCC operations are negligible for both penetration rates due to the light traffic. Nevertheless, due to the reduced header overhead, variant C also shows the best performance in this case.

The simulations performed in the rural environment also comprised an alternative implementation of the DCC FSM: rather than using five active sub-states, a linear adaptation of the packet transmission frequency is adopted, as highlighted in Table 6.2. However, as both implementation variants of the FSM performed almost identical in terms of the resulting awareness ratio and channel loads, the corresponding findings are displayed in appendix A.3. The maximum deviation of the awareness ratio never exceeded 1 % and the average effect on the channel load is below 0.1 %. Consequently, the resulting packet transmission rates due to DCC regulations have to be revised, when considering the transmission of a third message type on the CCH.

Summing up, *Collective Perception* exhibits a significant potential: regardless of the V2X market penetration rate, the vehicle's awareness can be increased. Even at very high market penetrations, shared sensor data is beneficial for certain ADAS applications. In combination with DCC operations, one might argue in both directions: on the one hand, DCC works as envisioned, as regardless of a third message sent on the same communication channel as the CAMs, awareness ratios due to CAMs are not affected and the resulting channel load is kept within limits. On the other hand, DCC blocks the transmissions of a significant number of these third messages, i.e. EPMs in this case. As a result, the awareness ratio due to *Collective Perception* is reduced significantly. However, as simulations with deactivated DCC for EPM transmission indicate, both the VANET and the employed protocol stack would be capable of handling the additional amount of data to be transmitted. Consequently, adaptations to the existing DCC algorithms are required, when transmitting any third message type on the CCH alongside legacy messages. Although accommodating additional information as part of extended CAMs might be an option to circumvent DCC operation, a dedicated data container inclusion management would also be required.

6.7. Summary

Collective Perception can only be realised, if the ad-hoc network between the ITS-Ss is able to transport the shared sensor data reliably. For analysing the capabilities of the VANET, this chapter first introduces a macroscopic simulation environment, focusing on resembling realistic motion profiles of the network nodes and on the representation of a complete ETSI ITS G5 stack for every communicating vehicle. The current chapter introduces the simulation framework Artery, which builds upon the Veins project. The simulation framework couples the dedicated traffic simulator SUMO with the network simulator OMNeT++. Artery adds support for the European communication stack and for dedicated modelling of different ADAS applications for the vehicles within the simulation. For analysing the effectiveness of shared sensor data, this chapter also introduces local perception sensors to the simulation framework which can be attached to the vehicles. Combining the vehicle's communication capabilities and the data gathered by these sensors, the concept of *Collective Perception* can be studied in great detail.

This simulation framework is employed in several extensive simulation studies to analyse the potential of *Collective Perception* and to identify constraints resulting from the ad-hoc network. Different traffic scenarios and parameters of the communication stack have been varied to find answers to the research questions introduced in section 3.1.

The findings of the simulation studies underline the potential of shared sensor data: in scenarios, in which only a limited number of vehicles are equipped with communication capabilities, *Collective Perception* increases the number of perceived objects significantly. The analysis also presents different effects resulting from *Collective Perception*, such as a virtual extension of a vehicle's perception range as well as the influence of different tracking durations for objects maintained in a vehicle's environment model.

The specific analysis of the influence of the employed ITS G5 protocol stack on the effectiveness of *Collective Perception* identified several shortcomings that need to be addressed by future releases of the stack. The Decentralised Congestion Control (DCC) mechanisms of the ITS G5 stack are identified to be the bottleneck: in case the EPM is transmitted along with the legacy messages (i.e. DENMs and CAMs) on the same communication channel, DCC causes messages to be dropped at higher layers, albeit the observed channel load is well within limits and therefore capable of accommodating an additional message. Different simulation runs demonstrate the fundamental effectiveness of DCC, as transmission of CAMs is unhindered despite the EPM being transmitted on the same communication channel. However, the findings also show that the transmission of any other message on the same channel for moderately increased channel loads is rendered unreliable. Therefore, rather than sending a separate message for the purpose of sharing sensor data, extending the CAM by those data containers required by *Collective Perception* demonstrates the best result.

7 Microscopic Analyses

Chapter 6 presented the potential along with possible limitations of shared sensor data in the context of an ETSI ITS G5 communication framework. To a certain extent, the presented findings are independent from the message format exchanged between the vehicles: although the format determines the resulting message size, the content of the message is irrelevant from the perspective of the network analysis. Consequently, deriving a holistic concept for *Collective Perception* requires more than an analysis of prospective network limitations: ADAS applications running on communicating vehicles also need to be provided with data that can actually be utilised in their algorithms. Hence, only if both aspects are addressed, exchanging sensor data in a VANET is expedient. At the same time, both aspects influence each other: on the one hand, updated sensor data needs to be provided frequently. Consequently, the network needs to be capable of transmitting the data reliably. On the other hand, the message size and transmission frequency requirements need to stay within limits for not to cause excessive channel utilisation.

Whereas chapter 6 analysed the macroscopic aspects of *Collective Perception* — the characteristics of the VANET between the ITS-Ss — this chapter focuses on the vehicle level: chapter 5 antedated the relevant message contents of *Collective Perception* resulting from the microscopic analyses presented in this chapter. An essential component for the realisation of *Collective Perception* at the vehicle level is an environment model, fusing local sensor data and providing an object list for the algorithms of ADAS applications. Section 7.1 proposes an architecture for implementing *Collective Perception* in the context of an automated vehicle. Exchanging sensor data between vehicles is only purposeful, if the receiving vehicle is able to locate remotely perceived objects accurately within its local reference frame. Therefore, section 7.2 presents the required coordinate transformations related to the proposed *Collective Perception* message format, along with an error propagation model to derive requirements regarding measurement accuracies. To identify the relevant objects to be included as part of the *Collective Perception* message format, the section additionally applies a concept from the literature to assess the plausibility of locally perceived objects. Eventually, the feasibility of the overall concept is demonstrated in section 7.3. For this purpose, the developed EPM format and the object fusion framework are implemented in automatically driving vehicles. The chapter also provides a performance analysis of *Collective Perception* in the context of an obstacle avoidance scenario with two automated vehicles on a race-track.

The analyses presented in this chapter are considered *microscopic*, as their scope comprises relevant steps for implementing *Collective Perception* in an actual vehicle. Although an ETSI ITS G5 stack is used for communication between the vehicles, effects resulting from the VANET are out of scope of this chapter but have been analysed in chapter 6. Most of the work presented in this chapter is primarily based on the following publications: [94, 107, 108].

7.1. Object Fusion Framework

Most of the following explanations in this section have been partially taken or adapted from [107].

In most of today's vehicles, local perception sensors feed their information directly to the ECU specific to an ADAS application: in case of an ACC application, for example, a front-facing Radar or camera sensor transmits its perceived objects via a CAN bus to the ECU providing the ACC functionality [41]. It is part of the algorithms running on this ECU to perform object tracking and data fusion tasks, e.g. in case multiple front-facing sensors are used. Every other application relying on the same sensor data but running on a different ECU, e.g. an emergency brake assist, has to conduct the same tasks, albeit the ECU of the ACC system already performs the required object tracking. However, in the scope of automated driving, this kind of architecture is no longer viable [234]. For SDSs, the longitudinal control, i.e. the responsibility of an ACC in level-2 vehicles, needs to be combined with lateral control, e.g. the responsibility of the lane-keeping system in level-2 vehicles. In addition to this functionality, a path-planning component has to determine the vehicle's long- and short-term trajectories which serve as the input to the longitudinal and lateral controller.

These applications require a common *knowledge base* — the environment model — providing an interpreted, non-ambiguous and up-to-date description of the vehicle's current surroundings. This leads to the following requirements:

Scalability Object fusion architectures of SDSs have to meet several demands for different products, markets and operation environments. Depending on the targeted SAE level of automation for a SDS, different sensors need to be integrated into the system. Hence, the architecture has to be able to provide different levels of automation with a varying number of perception components.

Modularity Contrary to some of today's ADAS applications, the components required to create a SDS cannot be integrated into a single ECU. Additionally, each component has different requirements regarding computation capabilities and functional safety aspects [142, 164]. Furthermore, several components, such as the scene interpretation and path-planning module need to be capable of remote-updates to comply with future requirements.

Real-Time Capabilities SDSs need to be able to react to changing environment conditions instantly. This requires processing and interpretation of numerous sensor data in a timely fashion. Consequently, the object fusion framework has to provide an updated representation of the current driving environment to the path-planning component in real time.

With the introduction of inter-vehicle communication, remote data needs to be considered by the object fusion architectures as well. This section presents an approach for integrating information received from other vehicles into the data fusion architecture of SDSs. Meeting the requirement of modularity, the architecture introduces several components that may be distributed to independent computing resources. The proposed modules may be used as an add-on to the components of an existing SDS, thereby introducing V2X capabilities.

The work presented by Rauch et al. combined three different object fusion components to generate a single global list of fused objects, including objects from local sensors and V2X communication [179]. This thesis, however, proposes an architecture providing two separate object lists, thereby focussing on the addition of V2X capabilities to the environment model. Separate object lists offer the benefit of validating objects perceived by V2X communication in case the objects are also located within the FoV of an ITS-S's local perception sensor. It is up to the applications employing these object lists to decide whether the ITS-S has to react to one of the objects. Data exchange between the proposed modules is realised by means of a Data Distribution Service (DDS) [131] which offers QoS guarantees in a real-time environment. Figure 7.1 depicts the proposed architecture. The succeeding subsections provide further details for each module.

It has to be noted that the following descriptions do not focus on the implementation of sensor data fusion algorithms. However, related work regarding the employed mathematical and programmatic implementation is provided, whenever applicable.

7.1.1. Local Perception and V2X Communication Components

In accordance to the *sensing and detection*, *planning* and *acting* architecture of SDSs without communication, the *Local Perception* component depicted in Figure 7.1 represents the sensing part. Several local perception sensors $S_1 \ldots S_n$ provide their current measurements to a centralised *Local Sensor Data Fusion* component which performs sensor-to-track data fusion processes, as detailed in [41, 198]. The output of the *Local Perception* component is a spatially and temporally aligned *Local Fusion (LF)* object list, containing information about all detected objects in the vicinity of the vehicle, described in the local vehicle reference frame as introduced in subsection 5.1.2. Additionally, the *Local Sensor Data Fusion* also provides a so-called *Association List (AL)* describing the association of sensor measurement data to objects tracked within the component. Depending on the sensor types perceiving these objects, the measurement data provides the perceived objects' dynamic states (e.g. velocity), relative positions to the host vehicle and their geometric dimensions. Additionally, these objects may also be matched to a high-fidelity map to be considered by the path-planner of a SDS [116, 242].

In 'common' architectures of SDSs, this information would be passed on directly to the scene interpretation, path-planner and vehicle control components, labelled *Applications* in Figure 7.1. With the addition of V2X communication, a new type of sensor is essentially added to the vehicle. However, contrary to local perception sensors, data received via V2X communication is not measured by the receiving ITS-S per se, but provided by the transmitting ITS-S itself. Consequently, a direct communication link allows for the exchange of explicit information rather than implicit information resulting from measurements by

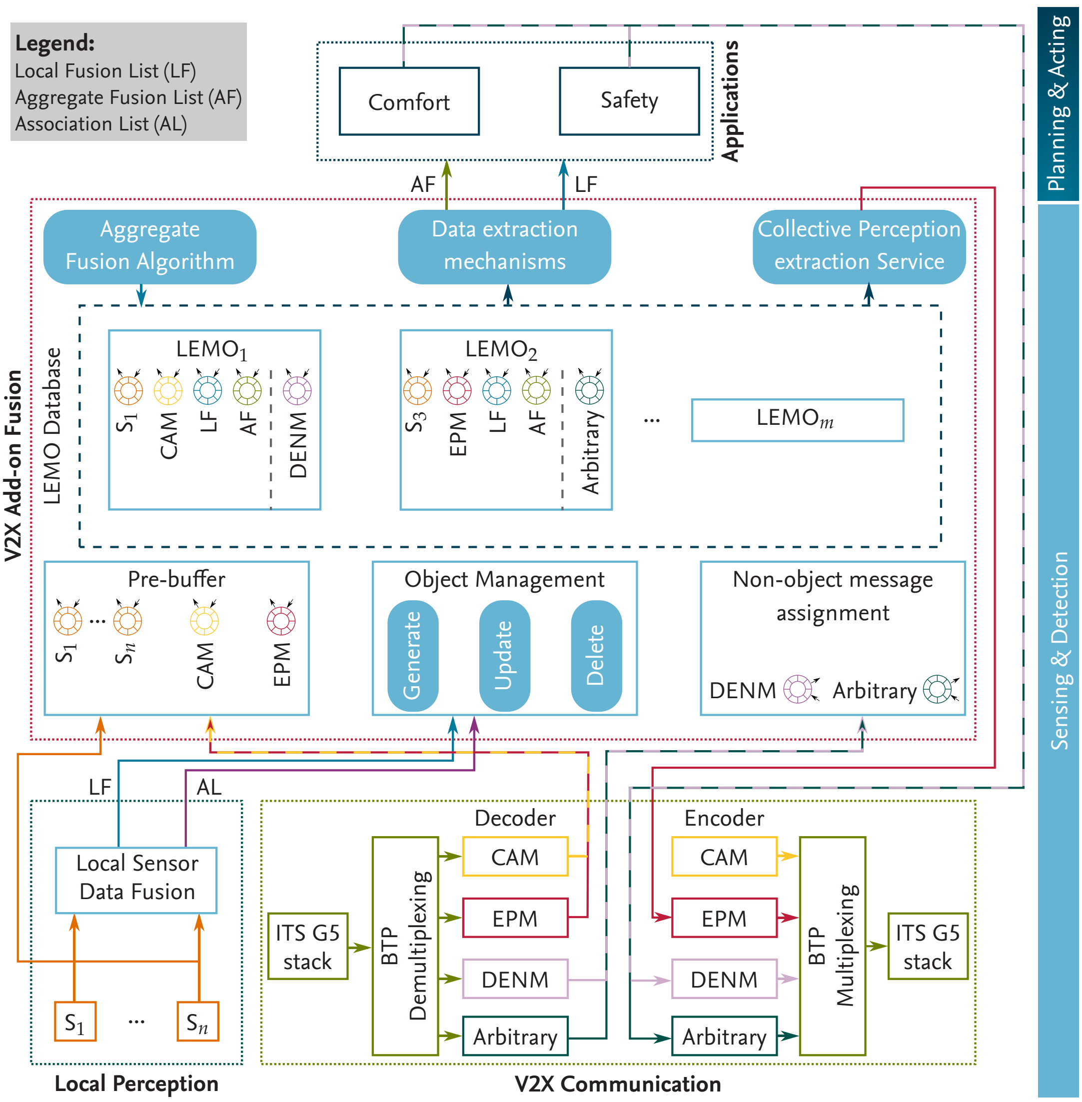


Figure 7.1.: Object Fusion Framework Architecture

on-board sensors about a perceived object. Furthermore, received messages do not necessarily contain data which may be employed in a data fusion process but are specific to an application [95]. Therefore, the developed architecture aims at providing a central instance responsible for both data fusion and storage of received messages for the applications of the ITS-S.

As depicted in Figure 7.1, a separate *V2X Communication* module is responsible for exchanging messages with other ITS-Ss. Upon receiving messages via the ITS G5 stack, the Basic Transport Protocol is used for demultiplexing the encoded data stream to specific decoding instances. The output of each decoder is a specific data structure containing the information of the received messages. As stated above, some of these messages contain information relevant to a data fusion process (e.g. CAMs and EPMs), whilst others such as the DENM and application specific data (Arbitrary messages) are relevant for certain applications only. At the same time, the *V2X Communication* module is also responsible for transmitting data to surrounding vehicles as well. For this purpose, data provided by other modules is encoded to the corresponding message formats, multiplexed with the help of the BTP and passed on to the ITS G5 stack.

7.1.2. V2X Add-On Fusion Component

For security reasons, the proposed architecture separates the process of fusing data from multiple local sensors from the process of fusing local sensor data with V2X information: in case of forged V2X data, such as false information sent by an attacker or unwittingly falsified position data [5], the environment model of a vehicle may be altered substantially. In a worst-case scenario, this might lead to faulty activation of safety-applications, such as an emergency brake system.

The *V2X Add-on Fusion* module depicted in Figure 7.1 serves as the backbone of the introduced architecture. This component has three tasks. First, storing the sensor data employed by the *Local Perception Object Fusion* for further processing and transmission. Second, providing the *Aggregated Fusion (AF)* object list, which resembles the LF object list enriched with information received via V2X communication. Third, providing the information for generating the EPM.

As stated above, the main principle of the component is based on the idea of a central module providing object and received message data for applications. The component consists of several constituents: as soon as new data is available from any local perception sensor, the corresponding measurement is not only delivered to the *Local Sensor Data Fusion* component, but also inserted into one of the so-called *Pre-Buffers* of the *V2X Add-on Fusion* module. This module provisions circular buffers for every local sensor for temporarily storing sensor data. As soon as the *Local Sensor Data Fusion* component is able to provide the updated LF object and association list based solely on the sensor data of the vehicle mounted sensors, the *Object Management* entity of the *V2X Add-on Fusion* is notified.

In conjunction with the working principles of the LEM presented in section 6.3.3, this entity is responsible for maintaining the *LEMO Database*. Based on the association and LF object list, the *Object Management* entity either creates, updates or removes LEMOs from the database. Hence, whenever an object is created by the *Local Sensor Data Fusion* component, a LEMO is created in the *V2X Add-on Fusion* module as well. Similar to the *Pre-Buffer* entity, each LEMO also maintains a unique circular buffer for every sensor contributing data to the corresponding object. Upon arrival of an association list, the *Object Management* entity assigns corresponding sensor measurements from the *Pre-Buffers* to the LEMOs. As a result, the framework maintains a history for every perceived object within the vehicle's vicinity, which may be accessed by the *Applications*. Additionally, the corresponding fused object description of the *Local Sensor Data Fusion* component is stored in a separate LF circular buffer: in the example depicted in Figure 7.1, LEMO_1 is perceived by sensor S_1 (e.g a front-facing Radar sensor), whilst LEMO_2 is only perceived by sensor S_3 (e.g. a rear-facing Radar sensor).

With the introduction of V2X communication, explicit information from other vehicles has to be processed as well. To bear resemblance to the arrival of updated local perception sensor data, received V2X messages containing object information (e.g. CAMs and EPMs) are also enlisted in a specific circular buffer within the *Pre-Buffer* entity. Afterwards, the *Aggregate Fusion* entity cyclically tries to associate the data in these message buffers to one of the existing LEMOs. For this purpose, the LF description in each LEMO serves as input data to a track-to-track fusion algorithm, as detailed in [198]. In case the data from a V2X message cannot be associated to one of the existing LEMOs in the database, a new LEMO is created. In the next step, the *Aggregate Fusion* entity generates the so-called AF description of the LEMO, combining data from local sensors and V2X messages. As a result, the AF object description contains both substitutional (e.g. the more exact object dimension information is taken from the CAM rather than from the local sensor measurement) and complementary data (e.g. position and velocity measurements provided by the CAM).

Received messages not containing information to be used by a fusion algorithm, e.g. DENMs or arbitrary messages, are passed on to the *Non-object message assignment* entity. This component utilises the station ID encapsulated in the V2X message to identify the corresponding LEMO from the database. In Figure 7.1, circular buffers for each received message type have been created in each LEMO: a DENM has been received from LEMO_1 and another arbitrary message from LEMO_2.

Whenever updates are no longer available for a LEMO, i.e. in case new messages or sensor measurements are no longer associated to one of the existing LEMOs, it is removed from the database after a grace period.

The purpose of assigning the initial sensor data employed in the data fusion process of a LEMO becomes evident in the context of *Collective Perception*. As discussed in section 5.4, rather than simply transmitting the LF object list, where the objects have been subjected to several filtering and prediction processes, the initial object description as provided by the sensor may be preferred. In case this feature is only of interest for research purposes, the LEMOs can be reduced to only provide circular buffers for object fusion lists and non-object messages.

7.1.3. Applications Component

The last component of the proposed framework consists of the actual ADAS or SDS applications, employing the provided object lists in their algorithms. LEMOs maintained and updated by the *V2X Add-on Fusion* module may by accessed by ADAS applications. For this purpose, a *Data Extraction Mechanism* entity provides an interface to the applications for accessing data. Contrary to today's ADASs, applications no longer have to care about sensor data fusion and object tracking aspects but request the relevant objects from the *V2X Add-on Fusion* module.

Depending on the type of application and its functional safety requirement, the architecture is capable of providing two different object lists: the LF object list consists of only those objects perceived by the local perception sensors of the vehicle and is hence equivalent to the output of the *Local Sensor Data Fusion* module. The AF object list contains all objects received via V2X, fused with those objects perceived by the local perception sensors. Whenever applicable, the information in the LF object list is enriched with information received via V2X (i.e. if a locally perceived vehicle can be matched to a V2X message, the geometric dimensions, light status, etc. can be merged with the sensor information). Whilst safety applications, such as an emergency brake assist, should mainly consider objects confirmed by local sensors, the LF object list is preferred over the AF list. ADAS applications increasing the driving comfort, such as a long-term route guidance or ACC systems, might use the AF object list instead. As the LoS of on-board sensors might be limited due to the current driving environment, the AF object list will generally contain object descriptions from the wider vehicle surroundings.

7.2. Transformations and Accuracy Analysis

As described in subsection 5.2.3, the data containers for *Collective Perception* envision the transmission of relative distances and dynamic variables of perceived objects in the sensor reference frame of the originator. Additionally, this information is accompanied by accuracy estimates for each variable. These requirements result from the working principle of the object fusion framework, as described in section 7.1. Subsection 7.2.1 describes the mathematical background to perform the required coordinate transformations in order to represent another vehicle's sensor data in the recipient's reference frame. However, remote sensor data is only suitable for ADAS applications, if the accuracy is within certain limits. Therefore, subsection 7.2.2 provides a mechanism for estimating the accuracy of a measurement in the recipient's reference frame. Prior to an EPM transmission, candidate objects to be included in the message need to be selected. As outlined in section 5.4, simply transmitting unfiltered, raw sensor data is thereby not an option, due to unreasonable bandwidth requirements. Instead, filtered and pre-processed object lists will be transmitted, for which the encapsulated objects have to fulfil certain quality and plausibility criteria. Consequently, subsection 7.2.5 presents the chosen mechanism to perform an estimation of an object's plausibility. This measure may then be used to identify objects to be included in the EPM.

7.2.1. Reference Frame Transformation

The coordinate transformation required to describe objects perceived by a remote ITS-S in the receiving vehicle's reference frame is a three-step process. It has to be noted that the following explanations describe the transformation of distance components only, as the corresponding transformations for other variables, such as the velocity and acceleration components, may be performed in a similar manner. Figure 7.2 depicts a scenario, in which a vehicle R receives object information from a vehicle T transmitting EPMs. The Figure also introduces the relevant reference frames of the transformation process. The gray-shaded areas resemble the vehicles' sensor frustums.

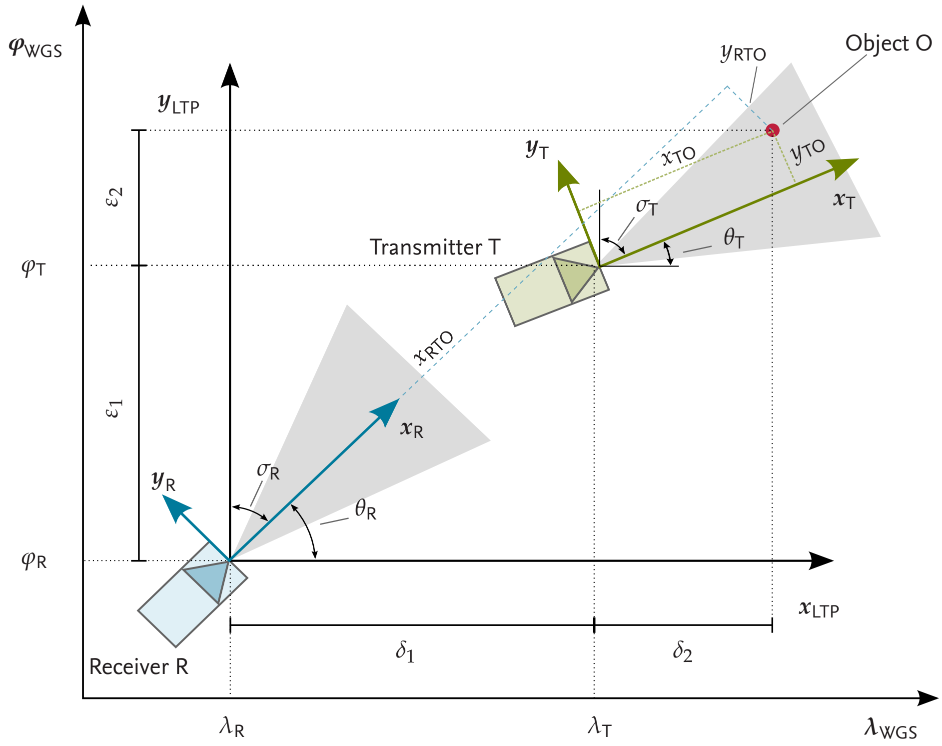


Figure 7.2.: Reference systems for *Collective Perception*

The first step determines the relative distance $(\delta_1, \varepsilon_1)$ from the receiving vehicle's global pose[1] $(\lambda_R, \varphi_R, \sigma_R)$ to the transmitter's global pose $(\lambda_T, \varphi_T, \sigma_T)$, both described in the WGS84 reference frame [163]. This can be solved by the inverse geodesic problem [200] in a LTP coordinate system (see subsection 5.1.2). Furthermore, using a local Cartesian reference frame for transforming the relative distance from the transmitting to the receiving vehicle does not require using the (generally) more inaccurate heading measurement [227]. As described in section 7.1, the relevant reference frame of the receiving vehicle's environment model is described by the basis vectors $\{\mathbf{x}_R, \mathbf{y}_R\}$ with a corresponding orientation of $\theta_R = 90° - \sigma_R$ with respect to the LTP reference frame.

The second step comprises the computation of the relative distance (x_{TO}, y_{TO}) between the transmitter T and its perceived object O, described in the transmitting vehicle's local reference frame with the basis vectors $\{\mathbf{x}_T, \mathbf{y}_T\}$. This distance also has to be transformed into the common LTP coordinate system by means of a simple active rotation: Using the relative orientation of the transmitting vehicle's local reference frame $\theta_T = 90° - \sigma_T$ and

1 A pose describes the combination of position (latitude φ_ζ and longitude λ_ζ) and orientation (heading) σ_ζ of the vehicle ζ at that position in the WGS84 reference frame.

the general rotation matrix $\mathbf{R}(\iota) = \begin{pmatrix} \cos(\iota) & -\sin(\iota) \\ \sin(\iota) & \cos(\iota) \end{pmatrix}$, the relative distance to the object can be calculated as

$$(\delta_2, \varepsilon_2)^T = \mathbf{R}(\theta_\mathrm{T})(x_\mathrm{TO}, y_\mathrm{TO})^T. \tag{7.1}$$

In the third step, the distance from the receiving vehicle to the object $(x_\mathrm{RTO}, y_\mathrm{RTO})$ can hence be calculated by simply adding the corresponding distance components described in the LTP reference frame, followed by a passive rotation into the receiving vehicle's local reference frame:

$$(x_\mathrm{RTO}, y_\mathrm{RTO})^T = \mathbf{R}(\theta_\mathrm{R})^{-1}(\delta_1 + \delta_2, \varepsilon_1 + \varepsilon_2)^T. \tag{7.2}$$

7.2.2. Data Quality

As introduced in section 5.2, all transmitted variables concerning the description of poses and dynamic states are accompanied by additional data fields for providing accuracy estimates. The rationale behind these provisions is to account for different requirements of both sensor data fusion algorithms and ADAS applications: objects perceived by others can only be considered by ADAS applications in case the location of objects can be provided with a certain accuracy.

Determining the relative pose between the object perceived by another vehicle and the recipient is crucial for ADAS applications. An exact description of the relative pose from a receiving vehicle to the objects perceived by a transmitter of an EPM, as depicted in Figure 7.2, is possible in case the underlying measurements are unbiased. Under this assumption, the coordinate transformation presented in the preceding subsection provides an exact relative pose. However, as for most real-world systems, sensors are subjected to different biases, resulting in inaccurate measurements. Furthermore, clock drifts contribute to further biases in the prediction process. As all vehicles consider the time provided by the GNSS receiver, the drift is neglected for the following explanations.

In general, two types of errors need to be differentiated: *random errors* occur as a result of several factors contained in every measurement, such as reading the scale, the location of the measurement device, etc. However, according to the central limit theorem, an estimation of the random error can be achieved by performing numerous measurements and by repeating an experiment. The dispersal of most random errors follows the common normal distribution [162]. *Systematic errors* result from non-observed and non-controllable environment conditions, causing different statistical parameters (mean and standard deviation) for every sample, even in the case of repeated measurements [162].

The three steps associated to the coordinate transformations in the context of *Collective Perception* as described in subsection 7.2.1 are subjected to different errors specific to the sensors providing the measurements. Whereas the pose information transmitted as part of the CAMs of the V2X enabled vehicles is provided by a GNSS-receiver and may be enhanced by an Inertial Measurement Unit (IMU), information about perceived objects is gathered with the help of local perception sensors, such as a Radar or a Lidar. Each data source is associated to measurement inaccuracies which propagate in case several measurements from different sources are combined.

The first step of the transformations, in which the relative distance components $(\delta_1, \varepsilon_1)$ between the transmitter and the receiver are calculated, relies on measurements of the global position of both vehicles. These measurements are provided by using a GNSS receiver. Without providing too much details, major systematic errors in the context of satellite-based position estimates result from different sources: *ephemeris errors* result from inaccurate knowledge about the satellites' positions. Despite being equipped with atomic clocks, *satellite clock errors* occur in the magnitude of 10 ns [253]. The time of travel of the GNSS signal is further influenced by *ionospheric* and *tropospheric effects*, which alter the speed of the signal. *Multipath effects* further reduce the accuracy of position estimates. Obstacles in the surrounding of the GNSS receiver, such as buildings, trees, etc. cause signals to travel on different paths to the receiver. The combined Root Mean Square (RMS) error of these effects commonly found in literature yields about 4 m [253]. Nevertheless, some of these effects can be compensated by using additional correction signals and IMUs, thus reducing the resulting measurement error up to a few centimetres [168, 253]. Furthermore, current research focuses on using high-fidelity maps in combination with local perception sensors to further enhance pose estimates [146, 153].

The second step relies on relative distance measurements $(x_{\mathrm{TO}}, y_{\mathrm{TO}})$ to detected objects of the local perception sensors mounted to the transmitting vehicle, which are rotated into the LTP system using the heading measurement σ_{T} of the transmitter. Average measurement errors of the local perception sensors are usually provided by the sensor manufacturers [40, 121, 188]. These errors are commonly in the order of a few centimetres, whilst the estimation of the vehicle's heading is based on a combination of consecutive position estimates and the consideration of acceleration components provided by IMUs. Consequently, a high-precision GNSS receiver combined with an IMU provides a heading measurement accuracy of up to 0.1° in a 1σ environment [168]. To put these figures into perspective, a common Radar sensor provides a measurement accuracy of about 10 cm, e.g. at a distance of 100 m [188]. However, a heading measurement inaccuracy of 0.1° adds about another 17 cm, when performing the coordinate transformation.

In the third step, where the transformed measurements in the LTP are combined and eventually rotated into the recipient's reference frame, these errors propagate in addition to the accuracy of the heading measurement σ_{R} of the receiving vehicle.

Simply adding the individual errors of each step results in a conservative estimation of the resulting overall error. As some of these errors are random and only occur in certain situations (e.g. multipath effects), mutual cancellation occurs — thereby reducing the overall expected error. Hence, the following explanations derive an error propagation model to both estimate the total resulting error and to perform an analysis regarding the required sensor accuracies.

7.2.3. Error Propagation Model

In conjunction with subsection 7.2.1, the following analysis focuses on the development of an error propagation model for position estimates. Error propagations for dynamic states occur in the same manner, albeit at a significantly smaller magnitude.

Describing pose errors Pose measurements can be modelled by probabilistic distributions, where the mean corresponds to the measured pose and the variance corresponds to the inaccuracy of the measurement. In the context of *Collective Perception*, multivariate distributions are required, as the pose and dynamic state of a vehicle or object ζ are described by several state variables. As such, the current pose is estimated as a vector $\boldsymbol{\mu}$ containing the measured poses within the local reference frame of the objects. For the V2X enabled vehicles transmitting and receiving EPMs, the mean is assumed to be zero, as the origin of the local reference frame translates according to the vehicle's movement. For the perceived object O, however, the mean values are the distance components of the sensor measurement $(x_{\mathrm{TO}},y_{\mathrm{TO}})$ described in the reference frame of the transmitter. For multivariate distributions, covariance matrices $\boldsymbol{C}_\zeta$ describe the mutual inaccuracies with respect to each measured variable. The covariance $\mathrm{Cov}(\rho,\tau)$ between all random real-valued and integrable variables ρ and τ is calculated as [162]:

$$\mathrm{Cov}(\rho,\tau) = E([\rho - E(\rho)][\tau - E(\tau)]). \tag{7.3}$$

The covariance describes the generalisation of the variance $\sigma_\rho^2 = E([\rho - E(\rho)][\rho - E(\rho)])$ in case of univariate distributions. $E(\cdot)$ describes the expected value of the random variable. If the random variable is described as a density function $\rho(x)$, the expected value is computed as [162]:

$$E(\rho) = \int_{-\infty}^{+\infty} x\rho(x)dx. \tag{7.4}$$

Figure 7.3 depicts the corresponding situation, in which all pose measurements are subjected to errors. As stated above, the likelihood of an object (e.g. vehicle or obstacle) ζ being located at the measured pose can be modelled by a multivariate normal distribution $\mathcal{N}(\boldsymbol{\mu}_\zeta,\boldsymbol{C}_\zeta)$. For the following analyses, the random variables of each measurement are considered to be distributed independently. Although it can be argued that at least the errors due to GNSS-measurements are not independent, as vehicles located in the same street are very likely to be subjected to similar signal propagation effects, the assumption of independence serves as a conservative estimation mechanism for the resulting combined error [162].

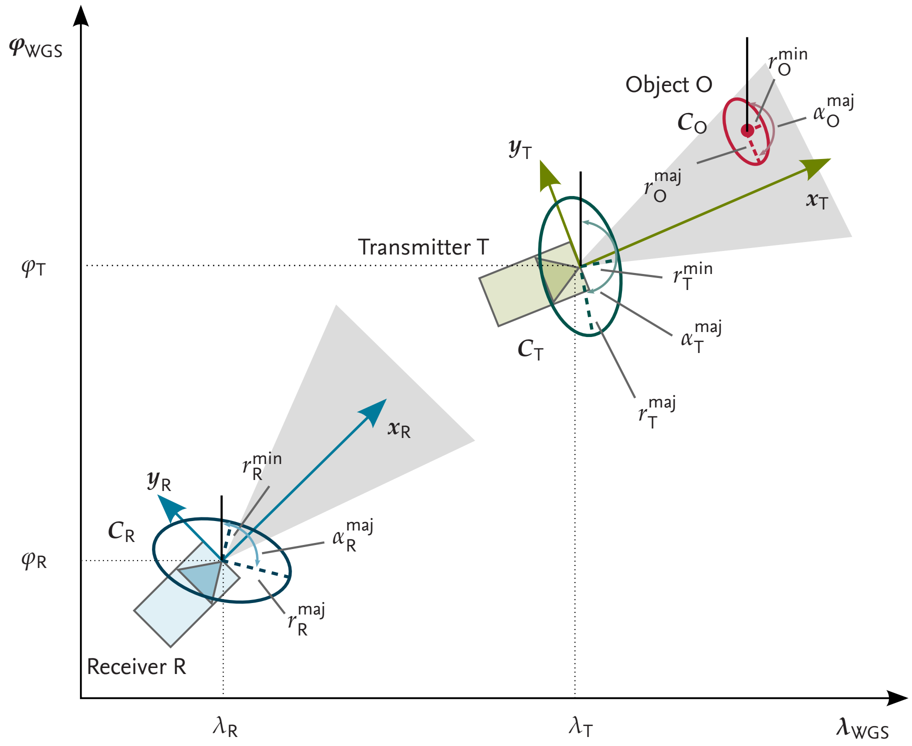


Figure 7.3.: Error ellipses

The following covariance matrices $\mathbf{C}_\zeta$ result for the description of the accuracy of the receiver R and the transmitter T in the depicted scenario:

$$\mathbf{C}_\mathrm{R} = \begin{bmatrix} \sigma^2_{x_\mathrm{R}} & \mathrm{Cov}(x_\mathrm{R}, y_\mathrm{R}) & \mathrm{Cov}(x_\mathrm{R}, \theta_\mathrm{R}) \\ \mathrm{Cov}(y_\mathrm{R}, x_\mathrm{R}) & \sigma^2_{y_\mathrm{R}} & \mathrm{Cov}(y_\mathrm{R}, \theta_\mathrm{R}) \\ \mathrm{Cov}(\theta_\mathrm{R}, x_\mathrm{R}) & \mathrm{Cov}(\theta_\mathrm{R}, y_\mathrm{R}) & \sigma^2_{\theta_\mathrm{R}} \end{bmatrix},$$

$$\mathbf{C}_\mathrm{T} = \begin{bmatrix} \sigma^2_{x_\mathrm{T}} & \mathrm{Cov}(x_\mathrm{T}, y_\mathrm{T}) & \mathrm{Cov}(x_\mathrm{T}, \theta_\mathrm{T}) \\ \mathrm{Cov}(y_\mathrm{T}, x_\mathrm{T}) & \sigma^2_{y_\mathrm{T}} & \mathrm{Cov}(y_\mathrm{T}, \theta_\mathrm{T}) \\ \mathrm{Cov}(\theta_\mathrm{T}, x_\mathrm{T}) & \mathrm{Cov}(\theta_\mathrm{T}, y_\mathrm{T}) & \sigma^2_{\theta_\mathrm{T}} \end{bmatrix}.$$

For the perceived obstacle O, the associated covariance matrix C_O is described in the reference frame of the transmitter. As the object is perceived by a local perception sensor which measures distance components only (next to dynamic parameters), a measurement of the heading component is unavailable:

$$\mathbf{C}_O = \begin{bmatrix} \sigma^2_{x_O} & \mathrm{Cov}(x_O, y_O) & 0 \\ \mathrm{Cov}(y_O, x_O) & \sigma^2_{y_O} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Covariance matrices can be visualised with the help of error ellipses [19], as shown in Figure 7.3 for the objects in the depicted scenario.

Principal Component Analysis Each covariance matrix is described in the basis of the local reference frame of each vehicle, i.e. $\boldsymbol{C}_{\mathrm{R}}$ is described in the basis $\{\mathbf{x}_{\mathrm{R}}, \mathbf{y}_{\mathrm{R}}\}$. Consequently, these matrices usually require all dimensional variables, e.g. the full covariance matrix for pose descriptions. However, the standardised ETSI ITS G5 messages only provide three variables for describing multi-dimensional inaccuracies: r_{ζ}^{maj} and r_{ζ}^{min} describe the dimension of the major and minor radius of the error ellipse along with the orientation $\alpha_{\zeta}^{\mathrm{maj}}$ of the major radius in the WGS84 reference system, as depicted in Figure 7.3. The inaccuracy of the heading measurement is provided separately along with the measurement variable.

For the purpose of deriving the error ellipse of a full covariance matrix, a dimension reduction mechanism is required. Covariance matrices can be processed by a Principal Component Analysis (PCA) to derive a new basis (components) describing the largest possible variance. A PCA performs a transformation in a way that the identified components are orthogonal to each other and hence provide an uncorrelated orthogonal basis set. Appendix A.2.1 provides a more detailed description of the working principles of a PCA. This set is then used to fully describe the 95 % ($\approx 2\sigma$) error ellipse as required by the ETSI ITS G5 standards [83]. However, as not all provided error approximations are necessarily scaled to this level, appendix A.2.2 additionally introduces a mechanism to scale standard deviations to a desired level.

Error estimation The derivation of an error estimation model in the context of *Collective Perception* is derived from Smith et al. [201]. Their work focuses on the estimation of propagated spatial uncertainty of a robot, whose current pose needs to be determined based on its last and current pose measurement. An estimation of a robot's pose is provided by (x,y,θ) along with an uncertainty (covariance) matrix $\boldsymbol{C}$. With each movement of the robot, the uncertainty of its current pose with respect to the global reference frame increases. Smith et al. introduce the term Approximate Transformation (AT) which describes the process of coordinate transformations in the context of uncertain measurement variables. The authors highlight that the mechanism of ATs outperforms a simpler best and worst case estimation of errors which adds the corresponding errors in each transformation step.

ATs have been adapted to the concept of shared sensor data in the context of V2X communication in [224, 225]. Consequently, the idea of a robot estimating its current pose with respect to a global reference frame is applied to the scenario depicted in Figure 7.2. In this case, (x_1, y_1, θ_1) describes the pose of the receiving vehicle with an associated covariance matrix $\boldsymbol{C}_1$ in its local tangential plane $\{\boldsymbol{x}_{\mathrm{LTP}}, \boldsymbol{y}_{\mathrm{LTP}}\}$. Similarly, (x_2', y_2', θ_2') along with the covariance matrix $\boldsymbol{C}_2'$ describe the pose and associated covariance of the transmitting vehicle T. Hence, in correspondence with equation 7.1, the required transformation to describe the pose of the transmitter in the receiver's reference frame yields:

$$\begin{aligned} x_2 &= f(x_1,y_1,\theta_1,x_2',y_2',\theta_2') = x_2' \cos\left(\frac{\pi}{180}\theta_1\right) - y_2' \sin\left(\frac{\pi}{180}\theta_1\right) + x_1, \\ y_2 &= g(x_1,y_1,\theta_1,x_2',y_2',\theta_2') = x_2' \sin\left(\frac{\pi}{180}\theta_1\right) + y_2' \cos\left(\frac{\pi}{180}\theta_1\right) + y_1, \\ \theta_2 &= h(x_1,y_1,\theta_1,x_2',y_2',\theta_2') = \theta_1 + \theta_2'. \end{aligned} \tag{7.5}$$

As stated above, these pose variables can be assumed to be random variables [201]. Consequently, the corresponding means of the estimation yield:

$$\begin{aligned} \bar{x}_2 &\cong f(\bar{x}_1,\bar{y}_1,\bar{\theta}_1,\bar{x}_2',\bar{y}_2',\bar{\theta}_2'), \\ \bar{y}_2 &\cong g(\bar{x}_1,\bar{y}_1,\bar{\theta}_1,\bar{x}_2',\bar{y}_2',\bar{\theta}_2'), \\ \bar{\theta}_2 &\cong h(\bar{x}_1,\bar{y}_1,\bar{\theta}_1,\bar{x}_2',\bar{y}_2',\bar{\theta}_2'). \end{aligned} \tag{7.6}$$

These functions are approximated by a first-order Taylor series expansion about the corresponding means [201]. As part of this process, the Jacobian $\mathbf{J}$ is employed to derive the corresponding covariance matrix:

$$\begin{aligned} \mathbf{J} &= \begin{bmatrix} \frac{\partial f}{\partial x_1} & \frac{\partial f}{\partial y_1} & \frac{\partial f}{\partial \theta_1} & \frac{\partial f}{\partial x_2'} & \frac{\partial f}{\partial y_2'} & \frac{\partial f}{\partial \theta_2'} \\ \frac{\partial g}{\partial x_1} & \frac{\partial g}{\partial y_1} & \frac{\partial g}{\partial \theta_1} & \frac{\partial g}{\partial x_2'} & \frac{\partial g}{\partial y_2'} & \frac{\partial g}{\partial \theta_2'} \\ \frac{\partial h}{\partial x_1} & \frac{\partial h}{\partial y_1} & \frac{\partial h}{\partial \theta_1} & \frac{\partial h}{\partial x_2'} & \frac{\partial h}{\partial y_2'} & \frac{\partial h}{\partial \theta_2'} \end{bmatrix} \\ &= \left[\begin{array}{ccc|ccc} 1 & 0 & -\frac{\pi}{180}y_2' & \cos\left(\frac{\pi}{180}\theta_1\right) & -\sin\left(\frac{\pi}{180}\theta_1\right) & 0 \\ 0 & 1 & \frac{\pi}{180}x_2' & \sin\left(\frac{\pi}{180}\theta_1\right) & \cos\left(\frac{\pi}{180}\theta_1\right) & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \end{array}\right] \\ &= [\mathbf{H}|\mathbf{R}(\theta_1)]. \end{aligned} \tag{7.7}$$

Consequently, the resulting covariance matrix expressing the combined uncertainty of the transformation in the global reference frame can be described by:

$$\mathbf{C}_{12} \cong \mathbf{J} \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2' \end{bmatrix} \mathbf{J}^T = \mathbf{H}\mathbf{C}_1\mathbf{H}^T + \mathbf{R}(\theta_1)\mathbf{C}_2'\mathbf{R}^T(\theta_1). \tag{7.8}$$

In the depicted scenario, θ_1 corresponds to the relative angle between the coordinate systems for which the transformation is performed. Hence, in correspondence to the transformation process outlined in subsection 7.2.1, multiple ATs are combined to derive a description of the resulting error model.

Two cases need to be differentiated: The first case only considers uncertainties, when combining the (inaccurate) pose measurements of the transmitter and the receiver. The second case applies to shared sensor data, where the object perceived by a transmitter is translated into the receiver's local reference frame.

Uncertainty of transmitter pose described in local reference frame of receiver This scenario applies for uncertainty estimates in case of transforming received poses by CAMs into the receiver's local reference frame. Only the inaccuracies associated to the GNSS-receiver providing pose measurements of both ITS-Ss need to be considered. For this transformation, the uncertainty of the heading estimation of the transmitter is irrelevant for the determination of the relative distance and has to be considered solely for the combined heading estimate. Hence, C_{T} is reduced to:

$$\tilde{\mathbf{C}}_T = \begin{bmatrix} \sigma^2_{x_{\mathrm{T}}} & \mathrm{Cov}(x_{\mathrm{T}}, y_{\mathrm{T}}) & 0 \\ \mathrm{Cov}(y_{\mathrm{T}}, x_{\mathrm{T}}) & \sigma^2_{y_{\mathrm{T}}} & 0 \\ 0 & 0 & \sigma^2_{\theta_{\mathrm{T}}} \end{bmatrix}. \tag{7.9}$$

As a result, the combined covariance $\mathbf{C}_{\mathrm{RT}}$ between the transmitter and receiver in the receiver's reference frame can be computed as:

$$\mathbf{C}_{\mathrm{RT}} = \mathbf{H}\mathbf{C}_{\mathrm{R}}\mathbf{H}^T + \mathbf{R}(\theta_{\mathrm{R}} - \theta_{\mathrm{T}})\tilde{\mathbf{C}}_{\mathrm{T}}\mathbf{R}^T(\theta_{\mathrm{R}} - \theta_{\mathrm{T}}). \tag{7.10}$$

Uncertainty of object pose described in local reference frame of receiver In this scenario, the combined uncertainty of an object perceived by a transmitter has to be represented in the receiving ITS-S's local reference frame. In addition to the GNSS-receiver's inaccuracies, the transmitter's sensor inaccuracies need to be considered as well. For this purpose, the *Dynamic Object* container of the EPM provides corresponding data fields. Consequently, in the first step, the uncertainty of the measurement performed by the local perception sensor $\mathbf{C}_{\mathrm{O}}$ of the transmitter is combined with the transmitter's pose uncertainty $\mathbf{C}_{\mathrm{T}}$. As measurements of the local perception sensor are already provided in the transmitter's local reference frame, the relative angle between the sensor's and the transmitting vehicle's reference frame is zero:

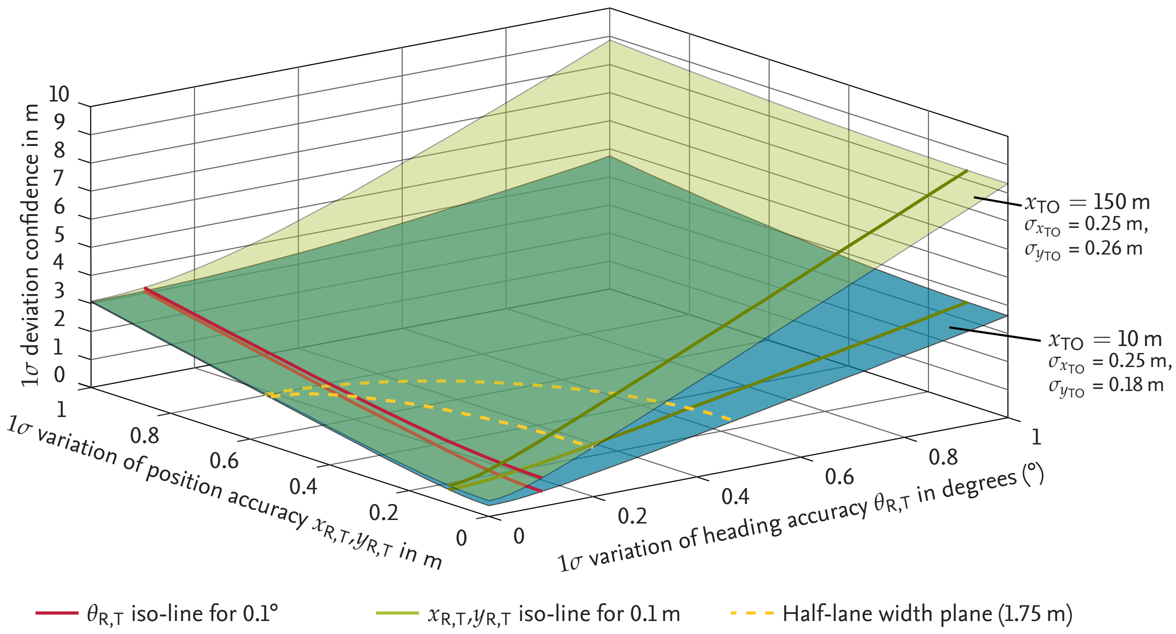
$$\mathbf{C}_{\mathrm{TO}} = \mathbf{H}\mathbf{C}_{\mathrm{T}}\mathbf{H}^T + \mathbf{R}(0)\mathbf{C}_{\mathrm{O}}\mathbf{R}^T(0). \tag{7.11}$$

In the second step, to calculate the object's pose uncertainty $\mathbf{C}_{\mathrm{RTO}}$ in the receiver's local reference frame, the receiver's pose uncertainty needs to be included as well:

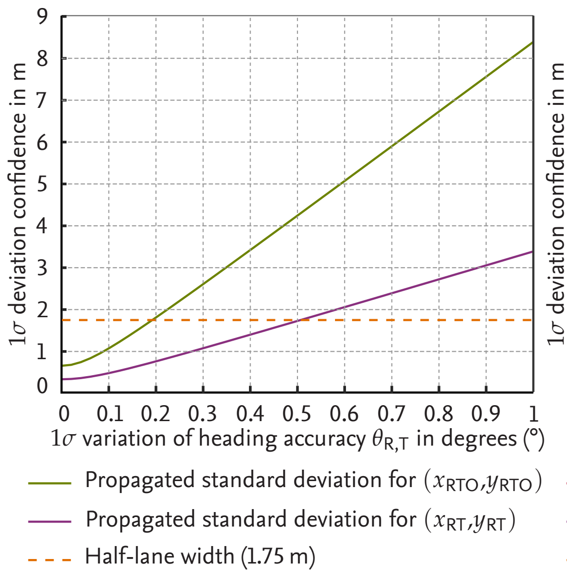
$$\mathbf{C}_{\mathrm{RTO}} = \mathbf{H}\mathbf{C}_{\mathrm{R}}\mathbf{H}^T + \mathbf{R}(\theta_{\mathrm{R}} - \theta_{\mathrm{T}})\mathbf{C}_{\mathrm{TO}}\mathbf{R}^T(\theta_{\mathrm{R}} - \theta_{\mathrm{T}}). \tag{7.12}$$

7.2.4. Accuracy Analysis

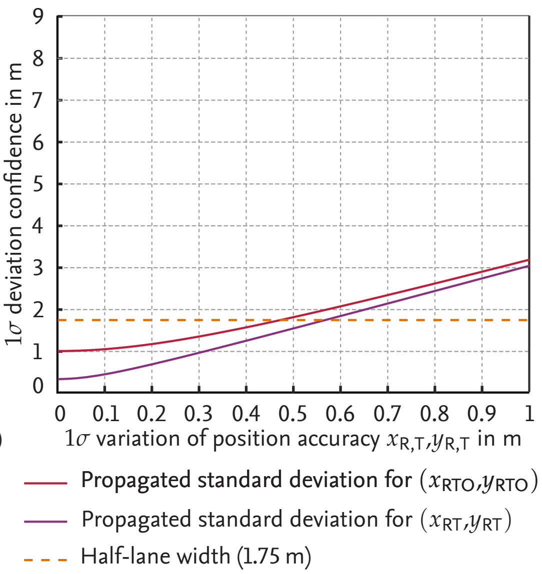
The derived error propagation model can be used to estimate the combined resulting error in the receiver's reference frame with respect to each measurement accuracy. As mentioned above, dependent error distributions and extinctions are not considered, thus resulting in a conservative estimation of the combined error. Figure 7.4 depicts the sensitivity analysis of the resulting 1σ ($\approx$68 %) deviation with respect to variations in the measurement accuracies of the pose description $(x_{\mathrm{R,T}}, y_{\mathrm{R,T}}, \theta_{\mathrm{R,T}})$ on the accuracy of the transformation of the object into the receiving vehicle's local reference frame. Along the abscissa in Figure 7.4a, the



(a) Sensitivity of 1σ ($\approx$68 %) deviation confidence for simultaneous accuracy variations in $x_{\mathrm{R,T}}, y_{\mathrm{R,T}}, \theta_{\mathrm{R,T}}$ at a distance $x_{RT} = 20$ m.



(b) Effect of heading accuracy on 1σ deviation confidence. (Iso-line for $\sigma_{x_{\mathrm{R,T}}} = \sigma_{y_{\mathrm{R,T}}}$ = 0.1 m at a distance of $x_{\mathrm{TO}} = 150$ m to the object).



(c) Effect of position accuracy on 1σ deviation confidence. (Iso-line for $\sigma_{\theta_{\mathrm{R,T}}}$ = 0.1° at a distance of $x_{\mathrm{TO}} = 150$ m to the object).

Figure 7.4.: Deviation confidence sensitivity analysis for different accuracy parameters with persistent local perception sensor accuracy.

heading measurement accuracy of both communicating vehicles, the receiver R and the transmitter T, are varied simultaneously. Similarly, the position measurement accuracy of both vehicles is varied along the ordinate. The resulting 1σ deviation confidence of the object's position in the receiver's local reference frame due to these variations is depicted along the applicate. The blue lower plane depicts the resulting error propagation for a distance between the transmitter and the object of 10 m. The green upper plane is the result of an increased distance to the object of 150 m. ADAS applications require an accurate description of objects in the vicinity of a vehicle. To derive the accuracy requirements of each pose measurement component, half of the width of a common road-lane in Germany (1.75 m [172]) is displayed. For the depicted error propagation, the measurement accuracy of the transmitter's local perception sensor is kept at the indicated constant level. In the depicted Figure, the Radar sensor provides 2σ accuracy values for distance measurements (0.25 m) and relative angular measurements (0.1°). Consequently, the lateral error increases with distance to the object [40].

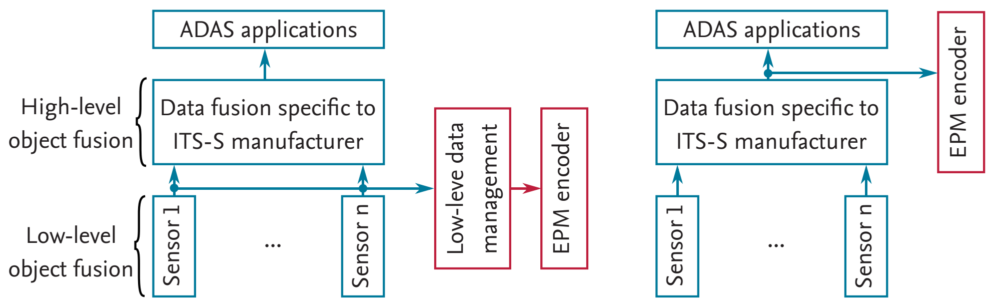
With increasing distance between the object and the transmitter, the resulting propagated error in the receiver's reference frame also increases. As displayed, reducing the accuracy of the heading measurement exhibits a prominent effect on the resulting propagated error. In combination with Figure 7.4b and 7.4c, the combined error can be analysed in more detail. As both Figures correspond to the indicated iso-lines in Figure 7.4a, inaccuracies for all pose variables are considered. The purple lines depict the propagated error due to the coordinate transformation of the transmitter's pose into the receiver's reference frame, i.e. $\mathbf{C}_{RT}$. As for this transformation, the heading inaccuracy of the transmitter is irrelevant (at least for the coordinate transformation of the position), larger inaccuracies are tolerable to receive a combined error within the limits of half a lane-width. However, the heading inaccuracy of the transmitter has a significant effect when transforming the object's position into the receiver's reference frame. At an object distance of 150 m to the transmitter and a position measurement inaccuracy of 0.1 m for the transmitter and the receiver, both communicating vehicles have to determine their heading with an accuracy of at least 0.2° for the propagated error to stay within the limit of half a lane-width. It should be noted that this is a conservative estimation, as compensations due to depending error distributions and error extinctions are not taken into account. Nevertheless, when selecting objects to be transmitted as part of a *Collective Perception* message, those closer to the disseminating ITS-S should be preferred to reduce localisation errors.

The depicted varied measurement inaccuracies are performed for both communicating vehicles simultaneously. Naturally, any other combination of measurement inaccuracies is possible, resulting in different error propagations. Nevertheless, with the knowledge about the sensor and GNSS-receiver accuracies, the presented methodology enables the transmission of measurement confidence levels, as envisioned by the ETSI ITS G5 standards. The confidence level of an object due to the error propagation model can be used by a high-level data fusion process, e.g. for weighting remote sensor data in the fusion process.

7.2.5. Object Plausibility

Next to the aspect of error propagation and the related question of the required measurement accuracies, another key aspect in the context of shared sensor data is the selection of those objects to be included as part of a prospective *Collective Perception* message. The proposed message formats presented in chapter 5 envision encapsulation of abstract descriptions of objects rather than raw sensor data (e.g. point-clouds) due to excessive data-bandwidth requirements [244]. Depending on the type of local perception sensor, different measurement principles apply. Manufacturers of automotive sensors usually perform a low-level sensor data fusion process on the ECU of the sensor itself. As part of this process, reflected Radar signals or point-clouds determined by a Lidar are used to run object detection algorithms. Based on continuously recurring measurements, objects can be extracted from the raw sensor data to provide a more abstract description of the perceived environment as a list of detected objects. The number of objects contained in the sensor object list typically varies frequently, as most objects can be perceived for a very short period of time only. To provide a more stable, enriched object list from several sources, sensor data is combined as part of a high-level object fusion framework, such as the one outline in section 7.1.

As mentioned above, the task of the high-level object fusion process is to continuously provide a temporally and spatially aligned list of abstract descriptions including all objects in the vicinity of the vehicle. However, this framework is specific to each ITS-S manufacturer. In the context of *Collective Perception*, this raises the question as to which level of the fusion process, data needs to be exchanged with other ITS-Ss. Figure 7.5 depicts the abstract layout of the data fusion architecture and possible extraction points for sensor data. As displayed, the object lists of the vehicle sensors are provided as input to the high-level object fusion framework which is specific to the manufacturer of the ITS-S. The output of the high-level fusion process is an object list containing a temporally aligned list of all detected objects in the vicinity of the vehicle. From here, two possibilities for



(a) Transmission of low-level sensor data

(b) Transmission of high-level sensor fusion data

Figure 7.5.: Abstract object data extraction levels for *Collective Perception*

extracting sensor data to be encapsulated as part of a *Collective Perception* message exist: the first option depicted in Figure 7.5a is the transmission of the latest available sensor data as provided by the local perception sensor, prior to any further data fusion process. In case of multiple sensors with different FoVs, a low-level data management entity is responsible for maintaining a list of the latest objects from each sensor-FoV. The second option depicted in Figure 7.5b, aims at directly exchanging the object list provided by the high-level data fusion framework. As this information is already employed by ADAS applications of the transmitting vehicle, receiving vehicles would be able to provide received information directly to their ADAS applications themselves.

Related to both approaches is the question of the required data quality associated to each object. Every manufacturer of ITS-Ss will have its own specific implementation of a high-level object fusion framework, consisting of different prediction and data fusion algorithms. Hence, high-level object lists cannot be compared in terms of their provided data quality, especially when information about the same object is received from several vehicles as the high-level fusion process subjects objects provided by local perception sensors to several low-pass filters. However, current research focuses on utilising different sensor accuracies to derive consolidated information about objects. Meuser et al. propose sharing not only a single measurement but also a probability vector associated to the current measurement [157]. Their approach introduces an accuracy metric suitable for combining noised measurement data from different vehicles. The metric also considers past and distant measurements to further enhance a more recent measurement. An important factor to be considered, especially for the process of standardising *Collective Perception*, is therefore the agreement on the data and corresponding accuracy information to be included as part of a prospective message format for *Collective Perception* to avoid filter cascades.

One possibility would be the definition of a common mechanism for estimating the plausibility of a perceived object. As part of this thesis, the concept of *Subjective Logic* has been applied to determine those objects to be included as part of the *Collective Perception* message. Only if the plausibility of a perceived object exceeds a certain threshold, it

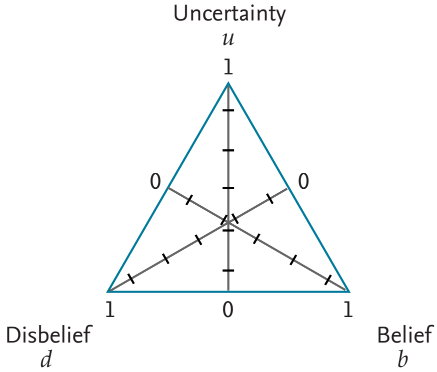


Figure 7.6.: Opinion Triangle according to [130]

will be included in the *Collective Perception* message. At the core of the concept stands a so-called *opinion triangle*, as depicted in Figure 7.6 [130]. The triangle is employed to model the likelihood of the existence of an object based on different opinions, i.e. different sensor data. Not only is a random variable assigned to a certain state (true or false), but also to an associated uncertainty about this state being correct. Contrary to common statistics (1-order probability), where a random variable expresses the likelihood, e.g. the existence of an object, *subjective logic* introduces the concept of 2-order probabilities to also provide a measure for the likelihood of the 1-order probability [130]. An alternative interpretation of a 2-order probability is the introduction of an uncertainty associated to the 1-order probability. Beta-probability density functions are used to model the corresponding 2-order probabilities [130].

Using this concept, each sensor s represents the existence of an object O by an opinion $\pi_O^s = \{b,d,u\}$ which satisfies $b + d + u = 1$, $\{b,d,u\} \in [0,1]$ [130]. The degree b to which a sensor believes to perceive an object thereby depends on the sensor's capabilities, such as its FoV and measurement accuracy. As part of the high-level object fusion process, different opinions, i.e. measurements from multiple sensors are combined to create an aggregate believe about the existence of an object. Without going into detail, subjective logic operators can be used to create the aggregate opinion, as detailed in [130].

Consequently, when standardising *Collective Perception*, the following aspects need to be addressed: first, the message format has to specify the abstract description of perceived objects, taking both network constraints and data fusion requirements into account. Second, manufacturers of ITS-Ss will only consider remote sensor data, if certain quality criteria for objects are met. This includes a common mechanism for describing combined uncertainty, as explained in subsection 7.2.2, as well as a specification of how object plausibility has to be estimated. Eventually, the concept has to be accepted by all participants and stakeholders and should therefore be addressed as part of ETSI standardisation efforts.

7.3. In-vehicle Verification

Most of the following explanations in this section have been partially taken or adapted from [107].

The microscopic analyses presented in this chapter were accompanied by several tests in actual vehicles. The following subsection 7.3.1 first introduces the scenario and set-up of the in-vehicle verification. Subsection 7.3.2 then details the empirical findings of the benefit of *Collective Perception* in the context of a collision avoidance scenario.

7.3.1. Scenario Description

The developed concept of *Collective Perception* has been validated as part of a research project which addresses highly dynamic automated driving scenarios on a race-track. As part of the project, two automated vehicles are placed on the track. Both vehicles are equipped with V2X communication capabilities based on the ETSI ITS G5 standards. V2X communication is employed for exchanging the vehicle's positions by means of legacy CAMs and for sharing planned trajectories. The latter is out of the scope of this document. Additionally, both vehicles were also equipped with identical front-facing Radar and Lidar perception sensors. The properties of the employed sensors are listed in Table 2.1 and Table 2.2.

Figure 7.7 depicts the developed architecture implemented in the vehicle. In conjunction with the architecture for cooperative driving, as introduced in section 2.3, the implemented components can be assigned to the three stages of *sensing and detection* of objects, *planning* and *acting*. The perception data of the local perception sensors is pre-processed by the sensors themselves, to perform low-level data fusion and to provide object representation in a common format. Afterwards, the sensor data is provided to the *Local Sensor Data Fusion* framework. Next to local sensor data, the vehicles are also able to receive V2X messages. For this purpose, the data received via the ITS G5 stack is passed to a demultiplexing component which distributes incoming messages to the corresponding message decoders, using the Basic Transport Protocol. Received trajectories from the other vehicle are passed to the *Trajectory Planner* component immediately. Along with the fusion result of the *Local Sensor Data Fusion* component, received CAMs and EPMs are passed on to the *V2X Add-on Fusion* component, as detailed in section 7.1. The object list provided by this component is then used by the *Trajectory Planner* to calculate the trajectory of the vehicle, taking potential obstacles on the track into account. The output of the planner is used by the *Vehicle Controller* to adjust longitudinal and lateral control of the vehicle. As the planned trajectory needs to be shared with other vehicles as well, this trajectory is also passed on to the *Trajectory Encoding* component. Additionally, EPMs need to be generated by each vehicle as well. For this purpose, the *V2X Add-on Fusion* component provides a list of objects to be transmitted to the *EPM Encoding* component. Encoded V2X messages are encapsulated in a GN packet and transmitted via the ITS G5 stack.

With one vehicle driving in front of another one, the FoV of the second vehicle might be obstructed. This not only restricts the detection area of the other vehicle, but also reduces the headway time for planning the vehicle's trajectory on the track. At the same time, this reduces the time available for reacting to potential obstacles on the track for the following

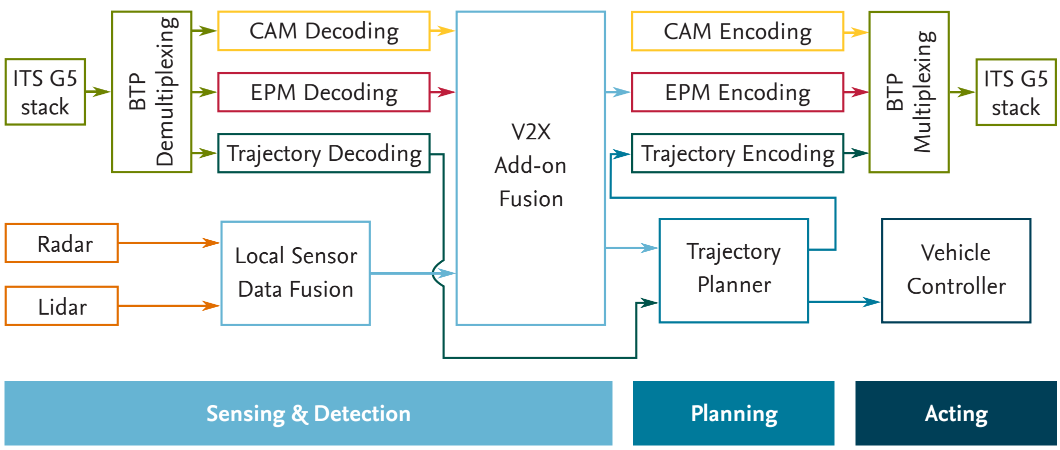


Figure 7.7.: Vehicle components architecture

vehicle. By sharing sensor data between both vehicles, *Collective Perception* alleviates these restrictions.

To demonstrate the benefit of sharing sensor data, an obstacle avoidance scenario is chosen. Figure 7.8 depicts the track on which the application has been developed and tested. As visualised, the obstacle is placed behind a turn on the track in such a way that the leading vehicle T (the EPM-transmitter) is able to perceive the object only a few seconds prior to a potential collision. Although T also transmits CAMs and its planned trajectory, the existence of the obstacle is only known to T, as the perception range of the host-vehicle R (the EPM receiver) is obstructed by T. Therefore, in addition to these messages, T and R also exchange EPMs as described in subsection 5.3.1.

As soon as the local perception sensors of the leading vehicle perceive the obstacle on the track and the object's plausibility, as outlined in subsection 7.2.5 exceeds a given threshold, e.g. 0.8, it is encapsulated in a perceived object container of the EPM. Consequently, the leading vehicle already perceives the object for a few milliseconds until it is chosen as a candidate to be transmitted as part of an EPM. Although the obstacle is not yet within the FoV of the host vehicle's local perception sensors, the path planning component is already aware of the presence of the obstacle and can therefore generate a safer and faster avoidance trajectory.

7.3.2. Performance Analysis

The displayed scenario has been evaluated in 26 runs around the race-track. The approach-speeds ranged from 60 km/h to 85 km/h for the leading vehicle and from 50 km/h to 75 km/h for the host vehicle, with corresponding distances of 40 m to 70 m between the ve-

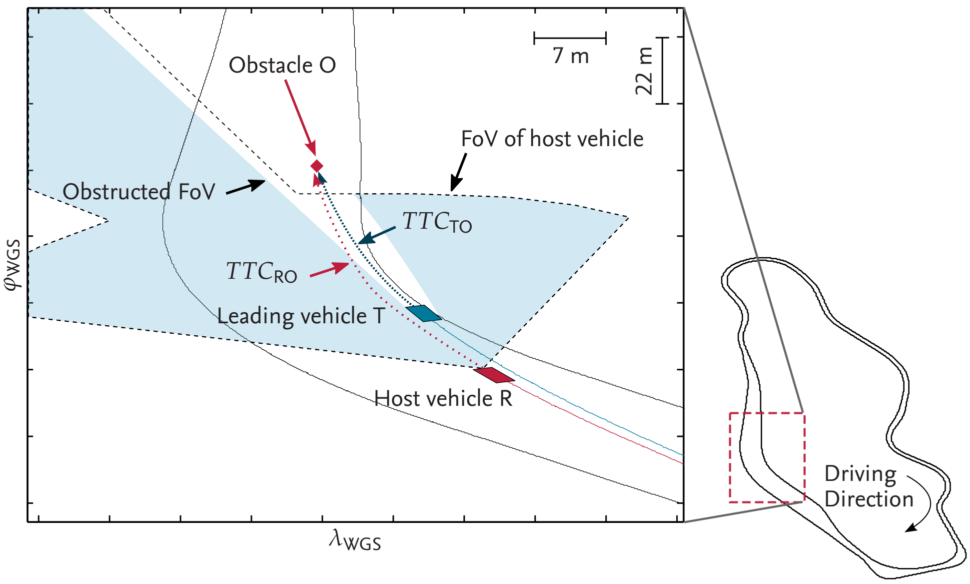


Figure 7.8.: Obstacle Avoidance Scenario

hicles. The combination of different approach-speeds and inter-vehicle distances therefore yields a representative dataset for heterogeneous driving situations.

Due to the identical local perception sensors mounted to the vehicles, it can be assumed that in the absence of the leading vehicle, the host vehicle also would have perceived the obstacle on the track, when itself located at the current position of the leading vehicle. Therefore, a comparison of corresponding Time To Collisions (TTCs) determined as soon as a vehicle perceives the obstacle, either by means of local perception sensors or by remote sensor data, provides a feasible methodology for analysing the benefit of *Collective Perception* in this scenario. Figure 7.8 also indicates the calculated TTCs. Given the current vehicle speed v and the distance d to the relevant obstacle, the prospective TTC can be calculated as:

$$TTC = \frac{v}{d}. \tag{7.13}$$

Consequently, the TTC of the leading vehicle T to the obstacle O (TTC_{TO}) therefore represents the minimum time available for planning a vehicle's trajectory to avoid the obstacle. Similarly, TTC^{*}_{RO} represents the time available to the host vehicle for avoiding the obstacle, when relying on its own local perception sensors only. Taking *Collective Perception* into account, TTC_{RO} can be calculated as soon as the host vehicle gains knowledge about the obstacle. In situations, where obscured perception ranges do not occur, i.e. the inter-vehicle distance is large enough or the obstacle is not yet within the sensor's perception range, *Collective Perception* still provides a benefit, as the host vehicle gains knowledge about the obstacle well in advance.

The screenshot of the development environment provided in Figure 7.9 shows the visualisation of the obstacle avoidance scenario from the host vehicle's perspective. In the depicted scenario, the host vehicle just gained knowledge about the obstacle placed on the track (red box) via an EPM received from the leading vehicle (orange and blue box). Furthermore, the host vehicle derives the leading vehicle's current FoV by utilising the FoV containers provided by the EPM (green shaded area). The host vehicle also perceives the leading vehicle by Radar (yellow dot on the rear bumper). Using the Radar data alone, further information about the leading vehicle such as its dimension would not be available. However, the leading vehicle is additionally perceived by CAM (orange box), providing the missing information. As a result, the *V2X Add-on fusion* component is able to combine both data sources to provide comprehensive information about the leading vehicle (blue box, displayed on top of the CAM representation).

Figure 7.10 depicts the corresponding performance analysis of the EPM for the scenario described above. The leading vehicle has a median available TTC_{TO} of 3.1 s to avoid the obstacle with the help of its local sensors in the current scenario. Without *Collective Perception*, the host vehicle's median TTC^{*}_{RO} yields 2.3 s. More significantly, in more than a quarter of the approaches, the vehicle would not have been able to detect the obstacle in time due to the current driving situation and obstructed FoVs. However, when sharing sensor data between vehicles, the time available for planning an avoidance trajectory is

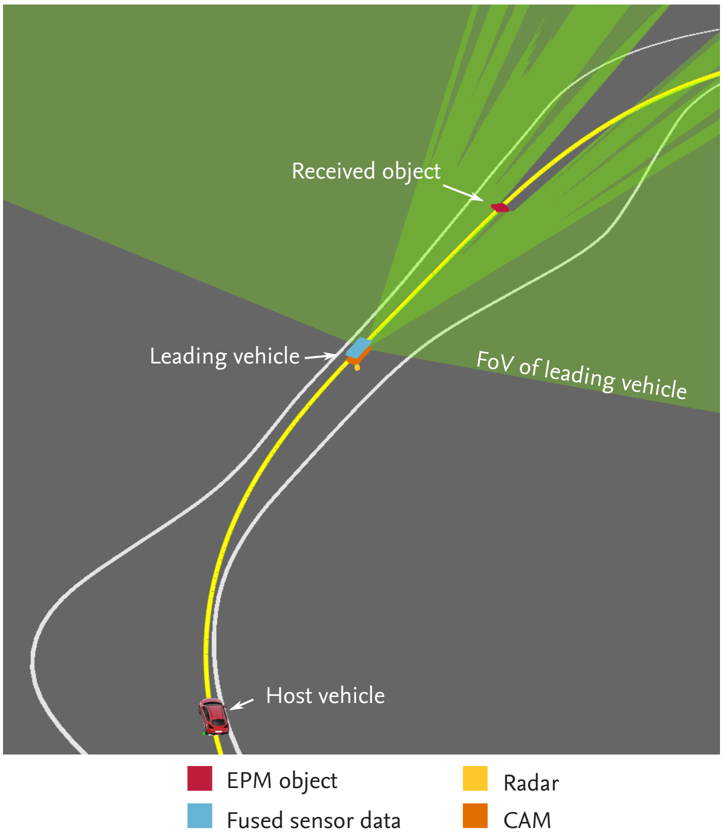


Figure 7.9.: Visualisation of the obstacle avoidance scenario from the host vehicle's perspective.

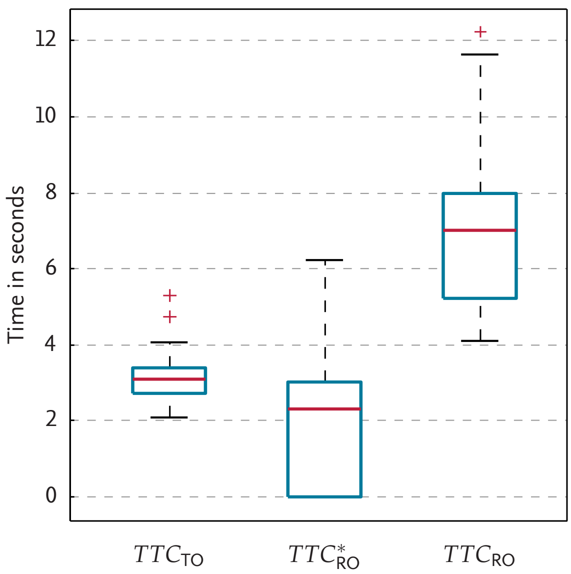


Figure 7.10.: Performance Analysis from 26 approaches

increased significantly: with a TTC_{RO} of 7.1 s, the available time for reaction is tripled, compared to the sensor-only scenario.

7.4. Summary

Whereas chapter 6 focused on the macroscopic analysis of *Collective Perception*, this chapter focuses on the microscopic vehicle level. For ADAS applications to consider remote sensor data, object descriptions need to be provided in a common format and with a certain quality. For this purpose, this chapter introduces a high level object fusion framework, adding V2X communication to a vehicle's sensory capabilities. The proposed framework serves as an environment model which collects all perceived sensor data, thereby creating a representation of the vehicle's current driving environment. The proposed architecture is capable of providing two separate object lists to the ADAS applications: the local fusion list contains descriptions of objects perceived by the sensors of the vehicle only. The framework also provides an aggregate fusion list, adding information received from other vehicles by means of V2X communication. This feature meets the concerns of safety applications which prefer relying on objects perceived by local sensors only. At the same time, providing two separate object lists allows for performing plausibility checks of objects received from other vehicles, e.g. in case this received object is also perceived by a vehicle's own on-board sensor.

Local and remote objects need to be represented in a vehicle's local reference frame. Therefore, this chapter also provides the required reference frame transformations, along with an error propagation model. Whilst measurements provided by on-board sensors are subjected to the sensor's measurement errors only, remote sensor data is additionally subjected to the errors of the pose estimates of the communicating vehicles, provided by a GNSS. The analysis shows that for the transformed location of a remote object to be accurate within the limit of half a lane-width, strict accuracies regarding the estimate of the global position and a vehicle's orientation (i.e. heading) need to be provided. Furthermore, this chapter also provides a discussion regarding the required quality criteria for an object to be considered by an ADAS application. Only if all participants employing the concept of *Collective Perception* (i.e. different OEMs) agree on a common metric for the plausibility of an object, remote sensor data can be trusted by applications.

To validate the concept, *Collective Perception* is implemented in two automated vehicles and applied to an obstacle avoidance scenario. As part of this implementation, the proposed EPM format is employed along with the object fusion architecture presented in this chapter. In the obstacle avoidance scenario, both vehicles share their local sensor data. As soon as the leading vehicle detects the obstacle, the following second vehicle is able to calculate an avoidance trajectory well in advance. The analysis of the scenario shows a significant increase in the resulting TTC compared to the first vehicle.

8 Conclusion

Vehicle connectivity will play an important role towards the expansion of self-driving vehicles. Whilst next generation cellular networks provide faster and more reliable internet access, a direct communication link between vehicles contributes to the realisation of truly cooperative driving applications as envisioned in chapter 2. This direct communication link is commonly referred to as V2X communication. Although today's vehicles may be equipped with a variety of on-board sensors to perceive their current immediate driving environment, the gathered information may only be used to imply (e.g. predict) future states, such as the position or behaviour of perceived traffic participants. V2X communication introduces the possibility of explicitly providing information about the current and future states of traffic participants, thereby taking the next step towards the realisation *Cooperative Driving*, as outlined in chapter 1.

However, even without partially or fully automated vehicles, V2X communication has the potential to reduce accident figures significantly [161, 217]. Consequently, vehicle manufacturers, suppliers and other players in the transportation sector teamed up to publish standards concerning the V2X communication protocol stack, exchanged message formats and working principles of prospective applications. In Europe, the ETSI took over the responsibility of the standardisation process and published the so-called ETSI ITS G5 standards. The first vehicles to be equipped with V2X communication will exchange their current positions and dynamic states as part of the Cooperative Awareness Message (CAM). Detected hazardous or abnormal situations can be broadcast via the Decentralized Environmental Notification Message (DENM). As a result, vehicles will be enabled to perceive their current driving environment not only with the help of their on-board perception sensors, but also with the help of V2X communication.

Consequently, local sensor data can be combined with the received information to provide a more comprehensive description of a vehicle's surroundings. This representation is called the *environment model* and continuously provides a list of perceived objects to ADAS applications. However, other traffic participants which are not able to communicate or are located outside of the FoV of a vehicle's local sensors, e.g. behind a building, are still not represented in a vehicle's environment model. Therefore, this thesis presents a concept for not only exchanging the current position and dynamic state of a communicating vehicle, but also for its local sensor data: this concept is called *Collective Perception*.

In the following, answers to the research questions formulated in chapter 3 are provided, summarising the key findings of this thesis in section 8.1. Furthermore, several further topics of research closely or remotely connected to *Collective Perception* have been identified. These topics are summarised in section 8.2.

8.1. Key Findings and Contributions

Based on the representation of the components of a cooperative vehicle, several research questions for the concept of *Collective Perception* have been presented in chapter 3. In the following, the key findings from every chapter for each research question are presented.

What is the potential of *Collective Perception*?

- The idea of sharing sensor data between other network nodes can be found in numerous disciplines. Chapter 4 presents the findings of an extensive systematic literature review, identifying four broader research areas in which shared sensor data is used for different applications. Whereas research in the area of **Wireless Sensor Networks** focuses on monitoring large scale facilities and on reducing energy consumption of network nodes, the areas of **Robotics** and **Defence** aim at tracking identified targets with the help of distributed sensors. In the area of **Automotive** research, multiple research projects pick up the idea of sharing sensor data between vehicles, albeit mostly specific to a certain ADAS application and not considering existing V2X standards. However, the fundamental consensus of the related work agrees on the potential of shared sensor data in the automotive context, albeit different implementations are proposed. Most of the concepts thereby either analysed different data fusion processes to combine remote sensor data with measurements of local sensors or focused on the development of applications incorporating shared sensor data. A specific analysis of constraints resulting from the communication stack, however, is not found.

- To be able to analyse effects resulting from the communication stack in great detail, section 6.2 introduces a **macroscopic simulation framework**, called *Artery*. The presented environment is based on the coupling of a dedicated traffic simulator with a dedicated network simulator and introduces the option of specifically simulating ADAS applications. For every vehicle in the traffic simulator, a complete ETSI ITS G5 communication stack is simulated as well. Hence, detailed analyses of the ad-hoc network between the vehicles can be performed.

- Employing this simulation environment for the analysis of *Collective Perception* entails **simulation of local perception sensors** attached to the simulated vehicles as well. Section 6.3 develops and implements an architecture for installing local perception sensors to the vehicles within the simulation. Consequently, data gathered from these sensors may be used by the ADAS applications running on these vehicles. In the context of *Collective Perception*, the development of prospective message formats is supported, as realistic message sizes can be computed when populating the messages with actually perceived objects.

- This simulation environment is employed in several extensive simulation studies presented in section 6.4. Multiple simulations have been performed with varying traffic scenarios to reveal the potential of *Collective Perception* on the basis of analysing the gain in a vehicle's awareness due to shared sensor data. Whereas with local perception sensors and exchanged CAMs, only communication enabled vehicles and those located within the FoV are known to a host vehicle, *Collective Perception* virtually extends a vehicle's perception capability beyond its current FoV. The presented analysis shows that with the help of *Collective Perception*, a **significant increase in a vehicle's awareness** can be observed even at low market penetration rates of communication enabled vehicles: to pick an example, the findings indicate that although e.g. only 10 % of the vehicles are equipped with communication capabilities, 35 % of the surrounding vehicles are on average known to a host vehicle due to *Collective Perception*.

Which limitations for *Collective Perception* result from the employed ETSI ITS G5 protocol stack?

- Answering this question is related to the question of possible message formats for realising *Collective Perception*. Only if the **resulting size of a message** can be estimated accurately, its effect on the communication channel can be analysed. Prospective message formats for sharing sensor data in a VANET are presented in section 5.3. The proposed **Environmental Perception Message (EPM)** represents a novel message format, consisting only of data relevant to realise the concept of shared sensor data. Several optional elements account for flexibility of the message, thereby reducing the resulting message size in case information may not be provided by a sensor. The message has been designed by using as many data fields from the already standardised ETSI CDD [83] as possible, thereby increasing compatibility with existing ITS G5 standards. Being a **separate message format**, the EPM can be disseminated on a separate communication channel other than the ITS G5 CCH for the purpose of distributing load. Alternatively, the data containers introduced by *Collective Perception* may be appended to the existing CAM. Although this approach increases **backward compatibility** for ITS-Ss not capable of decoding separate *Collective Perception* messages, it also increases the resulting message size significantly. On a general note, appending data containers to the CAM entails the need for a data inclusion management which has to be provided by the standardisation institutions as well.
- Both message formats have been analysed as part of the simulation study presented in section 6.6. The findings indicate that with respect to the resulting vehicle awareness, both variants appear to have similar effects. However, the simulations also considered effects resulting from the **Decentralised Congestion Control (DCC)** mechanism introduced by the ITS G5 standards, aiming at keeping the channel load within limits. When transmitting the legacy CAM and EPM on the same channel with DCC activated, the findings differed significantly. As **DCC restricts channel access**, message drops occurred for the EPM in favour of the CAM. Consequently, the corresponding vehicle awareness dropped significantly. However, when taking the observed channel load into account, this intervention would not have been required,

as the resulting channel load in the corresponding scenario without DCC is well within limits. In any case, appending the data containers of *Collective Perception* to the CAM exhibits both the highest vehicle awareness as well as the lowest observed channel load.

What information about objects perceived by other ITS-Ss need to be shared to be considered by the receiving vehicle's ADAS applications?

- The answer to this question is subjected to a **trade-off**: to increase network utilisation and to reduce bandwidth requirements, the *Collective Perception* message should be transmitted as seldom as possible and its corresponding size should be as small as possible. However, from the perspective of a sensor data fusion process or an ADAS application, updated information about detected objects should be provided as frequent as possible.

- The data required by coordinate transformation and data fusion processes governs the minimum set of variables to be included as part of a *Collective Perception* message. The identified data containers presented in section 5.2 contain a selection of variables to be included. To be able to relate remote sensor data to the transmitter, the **Originating Vehicle Container** encompasses position and dynamic state information about the perceiving vehicle. Its detected objects are encapsulated in the **Perceived Objects Container**. The minimum set of variables for the description of an object includes the relative distance and velocity components to the perceiving vehicle. Depending on the employed sensor technologies, several further optional data fields may be provided, such as an object's acceleration, geometric dimension or classification. Additionally, the **Field of View Container** provides information about the sensory capabilities of the transmitting vehicle. By combining received sensor FoVs of transmitting vehicles, an individual overall field of view can be inferred by every receiving vehicle.

What architectural requirements result from a real-time enabled environment model integrating *Collective Perception* in a vehicle?

- At the core of any ADAS application relying on the perception of a vehicle's environment stands the representation of the current driving environment — called the *environment model*. In section 7.1, an architecture for a high-level object fusion framework is presented. The proposed architecture is **scalable** to be able to process measurements from multiple sensors, whilst providing a high degree of **modularity** to distribute perception components to different computing resources. At the same time, the presented architecture provides **two separate object lists**: whilst the *local fusion* list contains objects perceived only by the vehicle's on-board sensors, the *aggregate fusion* list contains a more comprehensive description of the objects, enriched by received V2X information. This dissociation provides a **security mechanism in case erroneous or forged V2X data** deranges the vehicle's environment model.

- Existing architectures of environment models take the latest sensor measurements as input, process these measurements in a data fusion algorithm and cyclically provide a temporally and spatially aligned object list. However, in combination with *Collective Perception*, the environment model is also responsible for providing **a list of objects to be shared with other vehicles**. Simply sharing the object list provided by the aforementioned data fusion process is thereby unfeasible, as the corresponding state variables have been subjected to several low-pass filtering processes. Furthermore, associated covariances are often meaningless, unless the data fusion algorithm and its current state is known as well. As shared sensor data will be received by ITS-Ss of several manufacturers, each employing their own data fusion processes, the transmitted object data should be as close to the data provided by the sensor as possible. Therefore, the high-level object fusion architecture proposed in section 7.1 is able to provide both fused object descriptions as well as the corresponding original sensor data. Consequently, the developed environment model is capable of providing a list of original sensor measurements which have been associated to objects processed by a sensor data fusion algorithm. This list may consequently be shared with surrounding vehicles.
- Closely related is the question of the required object plausibility. The analysis of the ITS G5 communication stack presented in section 6.6 indicates limited capabilities regarding message size and transmission rates. Consequently, simply transmitting all objects perceived by a sensor — regardless of their existence probability — is unfeasible. As a result, a harmonised definition of **object plausibility** is required. Subsection 7.2.5 proposes to employ the concept of *subjective logic* to calculate the existence probability of a perceived object. Therefore, the corresponding number of objects included as part of a *Collective Perception* message can be reduced by selecting only those objects exhibiting a high existence probability. However, all parties contributing sensor data in a VANET have to agree on a common definition of *object plausibility* to be able to process remote data in a host vehicle's sensor fusion algorithms.

How can ADAS applications profit from the realisation of *Collective Perception* and what are its limitations?

- Several sources of errors exist along the path from a vehicle sharing its sensor data to the receiving vehicle: first, the data gathered about a detected object by the local perception sensor of the transmitting vehicle is subjected to measurement errors. Second, the provided global position of the transmitting vehicle, which is required for referencing its sensor measurement relative to the receiving vehicle, is subjected to GNSS errors. Third, similar GNSS errors also occur for the determination of the receiving vehicle's global position. Subsection 7.2.2 therefore provides an **error propagation model** which allows for the calculation of the overall resulting data accuracy, when combining all measurement errors. The presented sensitivity analysis reveals high requirements concerning the resolution of the heading accuracy, as small angular errors result in significant relative positioning errors for shared detected objects, especially at larger distances. However, with respect to prospective ADAS applications employing *Collective Perception*, different accuracy requirements exist: ADAS applications issuing warnings to the driver may impose lower requirements than highly automated ADAS applications.

- One representative of an application with high requirements has been developed in section 7.3: a **collision avoidance** application for automated vehicles on a race track demonstrates the capabilities of *Collective Perception* in an obstructed LoS scenario. In the given scenario, a vehicle on the track perceives an obstacle with the help of its on-board sensors and is able to calculate an avoidance trajectory. The perception range of a closely following vehicle, however, is limited by the leading vehicle and is only capable of perceiving the obstacle as soon as the leading vehicle veers out by following its avoidance trajectory. The empirical findings indicate that with respect to the boundary conditions of the scenario, the following vehicle might not be able to perceive the object in time. However, with *Collective Perception* enabled for both vehicles, the second vehicle gains significantly more time to calculate its avoidance trajectory.

8.2. Further Work

This thesis develops a holistic concept for sharing sensor data in a VANET: the relevant variables to be exchanged are identified and two novel (alternative) message formats closely following existing standards are introduced. These are thoroughly tested as part of macroscopic simulation studies. Furthermore, an architecture for considering remote sensor data by ADAS applications is presented. Nevertheless, several further issues should be addressed in consecutive research:

- **DCC adaptation:** As stated above, the simulation study presented in section 6.6 identified several shortcomings of the DCC algorithm proposed by the ETSI. Simply transmitting EPMs along with CAMs on the same communication channel causes DCC to drop messages in favour of reducing the resulting channel load. However, the findings of the same simulations with DCC deactivated indicate that the resulting channel load is still well within limits and should not cause the observed level of message drops. In fact, this finding affects any secondary message transmitted along with the CAM on the CCH and is not specific to sharing sensor data. Consequently, future standardisation efforts have to reconsider DCC mechanisms to allow for higher channel utilisation.

- **Update capabilities:** Throughout the associated research of the thesis, several versions of the CAM have been published by the ETSI. Some of these versions were not backward compatible with former versions. Considering that communication stacks of first-to-market vehicles are likely to include only DENMs and CAMs, it is important that these vehicles are capable of receiving updates. In case *Collective Perception* becomes standardised by the ETSI and DCC mechanisms are revised, vehicles already on the market will have to be updated as well. Hence, next generation vehicle architectures have to provide mechanisms for (remotely) updating at least the communication stack and ADAS applications considering V2X information.

- **Standardisation:** Several topics covered by the thesis may only be solved in cooperation with other stakeholders. Similar to the already standardised messages, a format for *Collective Perception* has to be published by standardisation institutions. This not only includes the specification of the ASN.1 syntax but also the corresponding guidelines of how to determine objects to be included as part of the prospective message. As discussed in section 7.2.5, simply transmitting the object list provided by object fusion algorithms is unfeasible. Hence, a common metric for defining object plausibilities and measurement accuracies has to be specified as well.

- **Security and Privacy:** When broadcasting sensor data, the question of whether remote data can be trusted and therefore utilised by the ADAS applications has to be answered. The ETSI envisions a Public Key Infrastructure (PKI) for authenticating ITS-Ss participating in communication in the VANET [119, 181, 236]. However, what happens if forged data is transmitted with a valid certificate? Furthermore, how can long-distance tracking of ITS-Ss be avoided, when intercepting traffic between the ITS-Ss? These questions have to be considered by a detailed security analysis which is out of the scope of this thesis.

- **Vulnerable Road Users:** The concept of *Collective Perception* is also suitable for publishing vulnerable road users, such as pedestrians, bikers and alike in the VANET. Key for the detection of vulnerable road users are specific classification algorithms [43]. For the purpose of also publishing these users in the VANET, it is the task of the disseminating ITS-S to detect, classify and transmit the vulnerable road users as part of a *Collective Perception* message. The *Perceived Object Container* proposed in this thesis already includes a classification variable which may be used to explicitly describe these road users.

- ***Collective Perception* on a global level:** In the context of FCD, *Collective Perception* may serve as an important data source. The concept presented in this thesis aims at increasing a vehicle's awareness for its environment by incorporating remote sensor data in its environment model. However, a significant leverage exists, when consolidating shared sensor data on a global level, e.g. on the back-end of an OEM or of some other institution. Some preliminary work following this concept is presented in [105, 214, 215]. As part of these publications, the Artery simulation environment is extended with LTE capabilities to cyclically transmit objects to a centralised back-end. The results of the presented simulations show that even for small market penetration rates of V2X enabled vehicles, a significant increase in the data quality on the back-end is achieved. The aggregated data on the back-end may be utilised by enhanced route guidance applications and traffic prediction models.

A Appendix

A.1. Environmental Perception Message ASN.1 Definition

```
EPM-PDU-Descriptions {
 itu-t (0) identified-organization (4) etsi (0) itsDomain (5) wg1 (1) en (123456) epm (2) version (1)
}

DEFINITIONS AUTOMATIC TAGS ::=

BEGIN

IMPORTS
   ItsPduHeader, ReferencePosition, Heading, Speed, SpeedConfidence, LongitudinalAcceleration, LateralAcceleration, VerticalAcceleration, StationType, VehicleRole, VehicleLength, VehicleWidth, YawRate FROM ITS-Container {
 itu-t (0) identified-organization (4) etsi (0) itsDomain (5) wg1 (1) ts (102894) cdd (2) version (1)
};

-- The root data frame for the environmental perception message

EPM ::= SEQUENCE {
 header ItsPduHeader,
 originatingVehicleContainer OriginatingVehicleContainer,
 fieldsOfView FieldsOfView OPTIONAL,
 perceivedObjects PerceivedObjects OPTIONAL,
 ...
}

FieldsOfView ::= SEQUENCE SIZE(1..10) OF FieldOfViewEntry

PerceivedObjects ::= SEQUENCE SIZE(1..20) OF PerceivedObjectEntry

OriginatingVehicleContainer ::= SEQUENCE {
 generationDeltaTime GenerationDeltaTime, -- 0..65535
 referencePosition ReferencePosition, -- see A.124
 heading Heading, -- see A.112
 longitudinalSpeed Speed, -- speed of disseminating vehicle in x-dir (see A.126)
 lateralSpeed Speed, -- speed of disseminating vehicle in y-dir (see A.126)
 vehicleLength VehicleLength, -- see A.131
 vehicleWidth VehicleWidth, -- see A.95
 ...
}

FieldOfViewEntry ::= SEQUENCE {
 sensorID SensorId, -- unique ID of sensor which is used to identify by which sensor an object has been perceived
 sensorType SensorType, -- Sensor type
 sensorPositionX SensorPositionComponent, -- longitudinal mounting point of sensor (-m)
```

```
  sensorPositionY SensorPositionComponent, -- lateral mounting point of sensor (-m)
  radius SensorRadius, -- perception radius of sensor (m)
  beginAngle SensorAngle, -- opening angle of sensor, right side
  endAngle SensorAngle, -- opening angle of sensor, left side
  ...
}

PerceivedObjectEntry ::= SEQUENCE {
  timeOfMeasurement TimeOfMeasurement, -- time (neg). since the object has been measured refered to GenDeltaTime (us)
  objectID ObjectId, -- Unique ID of object, persistent as long as object is tracked
  sensorID SensorId, -- Unique ID of sensor, corresponding to sensorID in FieldOfViewEntry
  objectDistX Distance, -- longitudinal Distance to object in sensor reference frame (m)
  objectDistY Distance, -- lateral Distance to object in sensor reference frame (m)
  objectSpeedX Speed, -- longitudinal speed of object in sensor reference frame (m/s) (see A.126)
  objectSpeedY Speed, -- lateral speed of object in sensor reference frame (m/s) (see A.126)
  objectHeading Heading OPTIONAL, -- Heading of object in WGS84 reference system if determined by model (deg) (see A.112)
  objectLogitudinalAcceleration LongitudinalAcceleration OPTIONAL, -- Longitudinal Acceleration of object, i.e. due to model (m/s2) (see A.116)
  objectLateralAcceleration LateralAcceleration OPTIONAL, -- Lateral Acceleration of object, i.e. due to model (m/s2) (see A.115)
  objectLength LengthDimension OPTIONAL, -- length of object if available (m)
  objectWidth WidthDimension OPTIONAL, -- width of object if available (m)
  objectType StationType OPTIONAL, -- classification of object if available (see A.78)
  ...
}

SensorType ::= ENUMERATED {
  undefined(0),
  radar(1),
  lidar(2),
  monovideo(3),
  stereovision(4),
  nightvision(5),
  ultrasonic(6),
  fusedObject(7),
  pmd(8)
}

GenerationDeltaTime ::= INTEGER { oneMilliSec(1) } (0..65535)

SensorPositionComponent ::= INTEGER {minusOneTenthMeter(-10), oneTenthMeter(10),
    unavailable(101)} (-100..101)

SensorRadius ::= INTEGER {oneTenthMeter(10), unavailable(4096)} (0..4096)

SensorAngle ::= INTEGER {minusOneTenthDegree(-10), oneTenthDegree(10), unavailable
    (3601)} (-3600..3601)

TimeOfMeasurement ::= INTEGER {oneMilisecond(1)} (0..15100)

ObjectId ::= INTEGER (0..255)

SensorId ::= INTEGER {unavailable(255)}(0..255)

SpeedDIN ::= SEQUENCE {
```

```
speedValue INTEGER {minusOneMeterPerSec(-10), standstill(0), plusOneMeterPerSec(10),
    unavailable(16383) } (-16383 .. 16383),
speedConfidence SpeedConfidence
}

Distance ::= SEQUENCE {
distanceValue INTEGER {minusOneTenthMeter(-10), oneTenthMeter(10)} (-32768..32767),
distanceAccuracy INTEGER {minusOneTenthMeter(-10), oneTenthMeter(10)} (-32768..32767)
}

LengthDimension ::= SEQUENCE {
lengthdimensionValue INTEGER {oneTenthMeter(10)} (0 .. 1023),
lengthdimensionAccuracy INTEGER {oneTenthMeter(10), unavailable(100)} (0 .. 100)
}

WidthDimension ::= SEQUENCE {
widthDimensionValue INTEGER {oneTenthMeter(10)} (0 .. 62),
widthdimensionAccuracy INTEGER {oneTenthMeter(10), unavailable(100)} (0 .. 100)
}

END
```

A.2. Principal Component Analysis and Scaling of Standard Deviations

The ETSI ITS G5 standard messages envision the description of covariance matrices in the form of error ellipses. In general, error ellipses are defined by the length of their major radius r_{ζ}^{maj} and minor radius r_{ζ}^{min} and follow the form

$$\left(\frac{x}{r_{\zeta}^{\text{maj}}}\right)^2 + \left(\frac{y}{r_{\zeta}^{\text{min}}}\right)^2 = 1. \tag{A.1}$$

The orientation of the major radius of the ellipse in the WGS84 reference system is provided by $\alpha_{\zeta}^{\text{maj}}$. However, most local perception sensors and GNSS receivers provide accuracy values for measurements in the form of covariance matrices or standard deviations only.

Subsection A.2.1 presents a mechanism for calculating an error ellipse from a covariance matrix as provided by a GNSS receiver. In subsection A.2.2, the principle for scaling standard deviations to a common level, as required for calculating error ellipses complying to ETSI standards, is presented.

A.2.1. Principal Component Analysis

As a dimension-reducing mechanism, a Principal Component Analysis (PCA) tries to represent multi-dimensional data by a reduced set of variables, whilst maintaining a high degree of variance of the original data set [2]. Furthermore, the mechanism is often used for the identification of 'hidden' patterns within a multivariate data set. The working principle of a PCA is based on the representation of the original data as a set of orthogonal variables [2]. For this purpose, a new basis is calculated, in which each axis is called a *principal component*. Each component thereby describes as much of the original data's variance as possible. In the context of this thesis, the PCA is used to rotate the calculated covariance matrix associated to the position of a received object by means of the *Collective Perception* mechanism into a reference frame complying with existing ETSI ITS G5 standards. This rotation is required, as a full covariance matrix cannot be transmitted as part of the standardised ETSI messages.

Instead, the ETSI envisions sending of error-ellipses for a two-dimensional normal distribution for describing the position accuracy, as outlined in equation A.1. This ellipse then needs to be scaled to a certain confidence level (e.g. 95 %). However, rather than using error ellipses, GNSS receivers commonly provide covariance matrices for the description of position inaccuracies.

Nevertheless, a covariance matrix $\boldsymbol{C}$ can be transformed to derive the description of the required error ellipse. For this purpose, $\boldsymbol{C}$ will be subjected to a PCA. Calculating the new basis into which the original covariance $\boldsymbol{C}$ will be transformed is based on the eigen-decomposition of positive semi-definite matrices [2]. The PCA relies on finding a matrix $\boldsymbol{X}$, such that

$$\boldsymbol{X}^T \boldsymbol{C} \boldsymbol{X} = \boldsymbol{D} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}. \tag{A.2}$$

The matrix $\boldsymbol{D}$ is a diagonal matrix and the columns $\boldsymbol{x}_i$ of $\boldsymbol{X}$ are orthogonal vectors of unit length. The elements of the diagonal of $\boldsymbol{D}$ are the eigenvalues of $\boldsymbol{C}$ and the columns of $\boldsymbol{X}$ are the corresponding eigenvectors. In this transformation, the eigenvectors then provide the orientation of the radii of the error-ellipse, whilst the eigenvalues describe the squared lengths of the radii for a 1σ confidence level, i.e. the variance.

Given a quadratic covariance matrix $\boldsymbol{C}$ of a data set centred about its mean, its eigenvalues λ_i can be found by solving

$$(\boldsymbol{C} - \lambda_i \boldsymbol{I})\boldsymbol{x}_i = 0, \forall \lambda_i, \tag{A.3}$$

where $\boldsymbol{x}_i$ represents the eigenvector for which the expression is valid. With $\boldsymbol{C}$ being a positive semi definite matrix, negative eigenvalues cannot occur [2]. Hence, for the non-trivial solution ($\boldsymbol{x}_1 \neq \boldsymbol{0}$), the first step consists of finding the eigenvalues λ_i by calculating the determinant of

$$|(\boldsymbol{C} - \lambda_i \boldsymbol{I})| = 0. \tag{A.4}$$

Solving this *characteristic equation* provides the corresponding eigenvalues λ_i. Each eigenvalue represents the corresponding variance of the identified components.

The determined eigenvalues can then be used in equation A.3 to calculate the corresponding eigenvectors $\boldsymbol{x}_i$. The rows of $\boldsymbol{X}$ correspond to these eigenvectors, sorted in descending order with respect to the corresponding eigenvalues, such that $\lambda_{1,1} \leq \lambda_{2,2}$.

As the original covariance matrix $\boldsymbol{C}$ is described in the local reference frame $\{\boldsymbol{x}_\zeta, \boldsymbol{y}_\zeta\}$ of vehicle ζ, the determined eigenvectors are described in the same basis. Consequently, the associated relative rotation angle α^{maj} between the $\boldsymbol{x}_\zeta$ axis of the original basis and the abscissa of the new basis $\boldsymbol{x}'_\zeta$ describing maximum variance can be found by determining the orientation of the eigenvector $\boldsymbol{x}_1$ associated to the first eigenvalue:

$$\alpha^{\text{maj}} = \begin{cases} \tan^{-1}(\frac{x_{1,2}}{x_{1,1}}), & \text{for } x_{1,1} \neq 0 \\ 90°, & \text{for } x_{1,1} = 0 \end{cases}. \tag{A.5}$$

Figure A.1 depicts the working principle of the PCA for vehicle ζ. With the help of the PCA, the covariance matrix provided by the GNSS receiver described in the basis $\{\boldsymbol{x}_\zeta, \boldsymbol{y}_\zeta\}$ is transformed to a diagonal matrix described in the basis $\{\boldsymbol{x}'_\zeta, \boldsymbol{y}'_\zeta\}$. The squared lengths of the radii of the error ellipse corresponding to the vehicle's current global position $(\varphi_\zeta, \lambda_\zeta)$ thereby correspond to the eigenvectors of the initial covariance matrix. To determine the

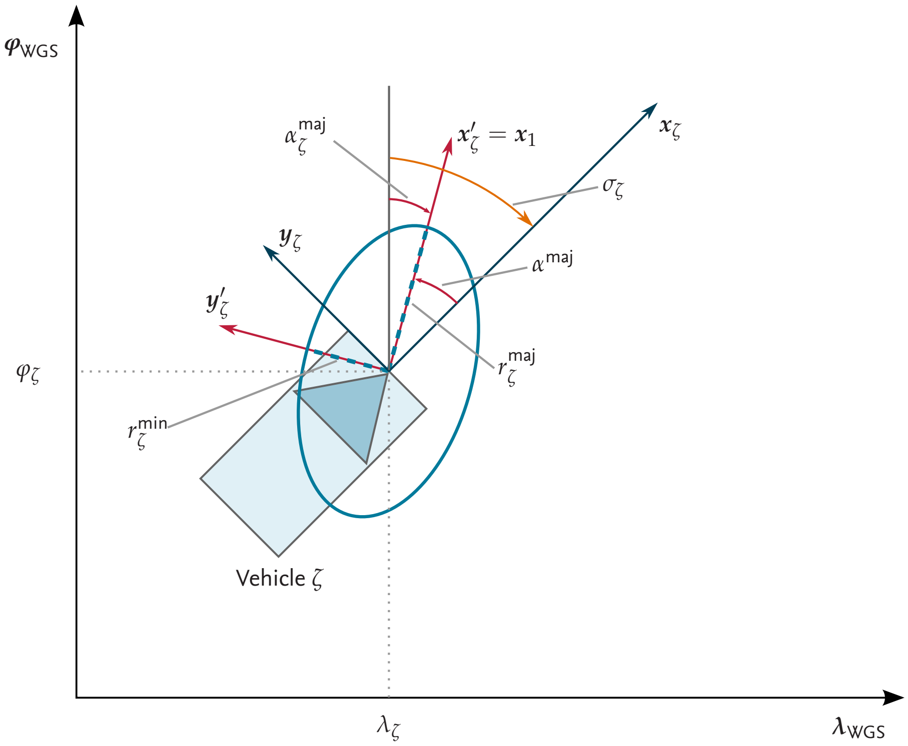


Figure A.1.: Principal Component Analysis and 95 % confidence ellipse

global orientation of the vehicle's position error ellipse α_ζ^{maj}, as required by the ETSI, the vehicle's global heading σ_ζ needs to be added:

$$\alpha_\zeta^{maj} = \alpha^{maj} + \sigma_\zeta. \tag{A.6}$$

A.2.2. Scaling Variances to Different Confidence Levels

Eigenvalues can be interpreted as the spread of the data along the direction of the extracted eigenvectors [129]. As stated above, the PCA represents a mechanism to derive diagonal representations of the original covariance matrix. These rotated matrices may then be used to derive corresponding error ellipses, as stated in equation A.1. In the context of *Collective Perception*, error ellipses result from the combination of several measured variables, each sampled from a normal distribution. Within the context of ITS G5 standards, these error ellipses have to be scaled to represent a 2σ confidence level, i.e. the object is located within the defined error ellipse with a probability of about 95 %.

Scaling a given standard deviation to a desired level can be achieved by utilising the χ^2 distribution, representing the sum of squared normal distributions (as it is the case for error ellipses) [129]. Specifying the degrees of freedom $k = 2$, as the error ellipse represents the uncertainty in two directions, the Cumulative Distribution Function (CDF) of the χ^2

distribution can be used to calculate the required confidence level s[1]. Consequently, with the two eigenvalues λ_1 and λ_2, where $\lambda_1 > \lambda_2$, the major and minor radius of the error ellipse evaluate to

$$\begin{aligned} r_\zeta^{\mathrm{maj}} &= \sqrt{5.991\lambda_1}, \\ r_\zeta^{\mathrm{min}} &= \sqrt{5.991\lambda_2}. \end{aligned}$$

1 For a 2σ ($\approx$95 %) confidence level with $k = 2$, the χ^2-CDF evaluates to 5.991: $P(s < 5.991) = 1 - 0.05 = 0.95$

A.3. Findings for Continuous Active DCC FSM

The following Figures depict the findings of the simulation studies presented in section 6.6, using a continuous active state for the DCC FSM. Figure A.2 depicts the resulting effect on the awareness ratio, as defined in subsection 6.4.3. As depicted, the maximum deviation for the awareness ratio never exceeded 1 %. Furthermore, the average effect on the channel load is below 0.1 %, as shown in Figure A.3.

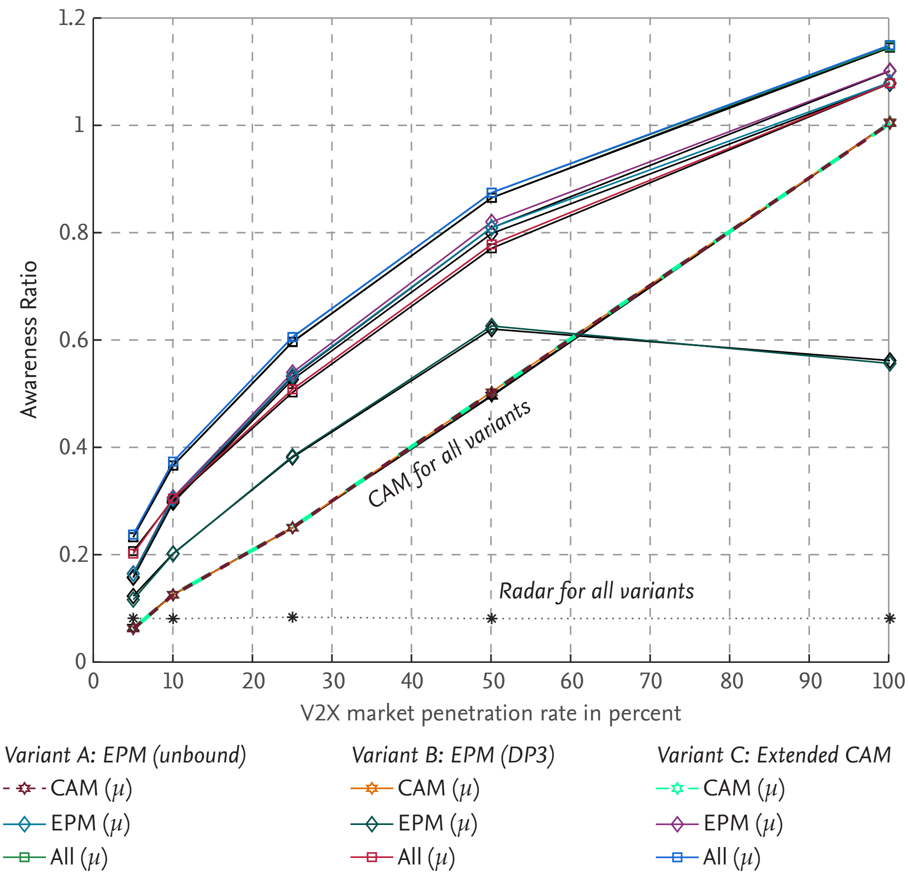


Figure A.2.: Effect of a continuous active state FSM on the awareness ratio with respect to the simulation variants. Black lines indicate the corresponding lines of Figure 6.15.

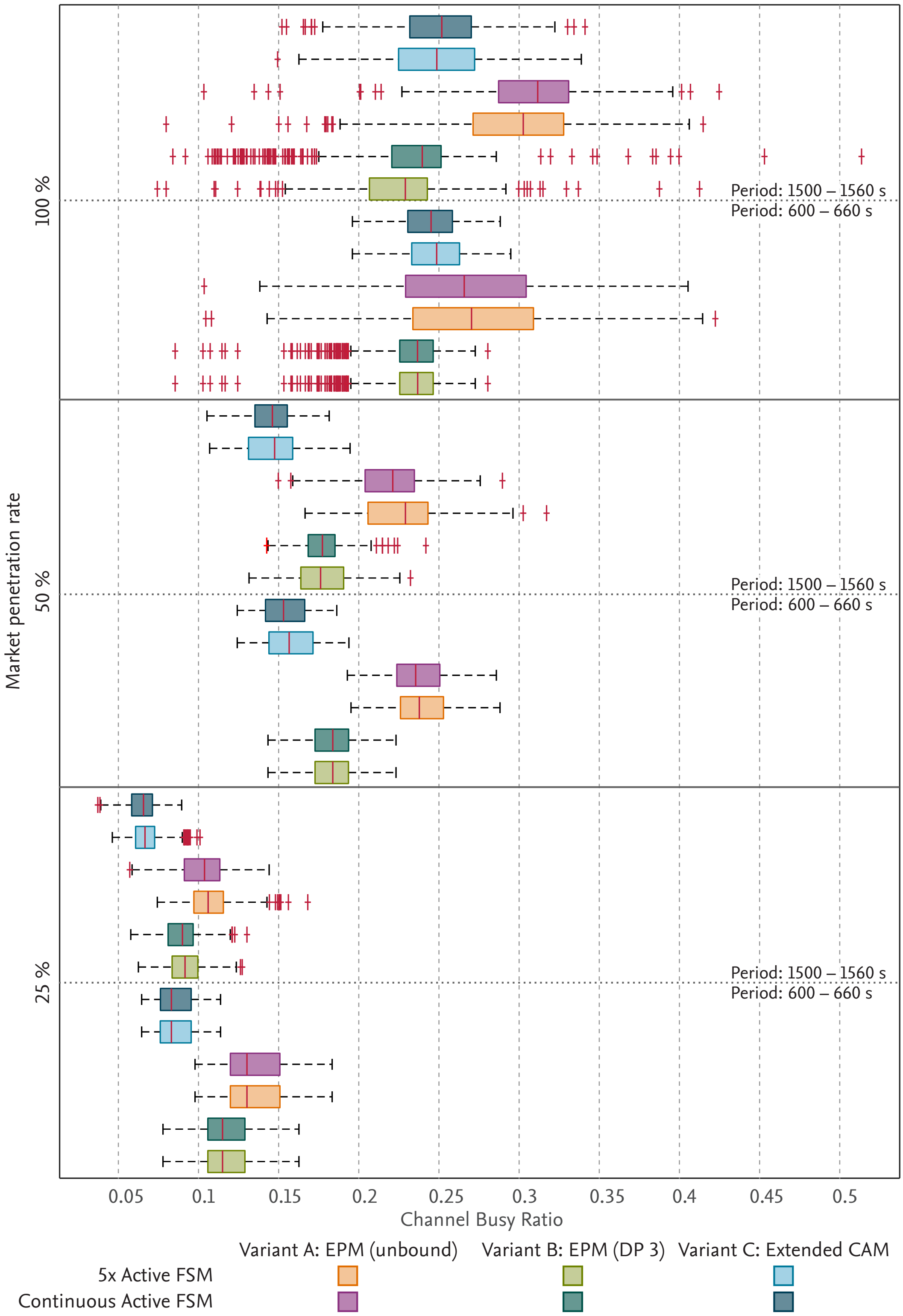


Figure A.3.: Overview on resulting channel busy ratio for different market penetration rates and dissemination variants for both DCC FSM implementations.

Bibliography

[1] 5G Infrastructure Public Private Partnership. *5G Automotive Vision*. 2015.

[2] H. Abdi and L. J. Williams. 'Principal component analysis'. In: *Wiley interdisciplinary reviews: computational statistics* 2.4 (2010), pp. 433–459.

[3] O. Aboutalib. 'Cooperative fusion architecture in a network centric environment'. In: *15th International Conference on Information Fusion (FUSION)*. 2012, pp. 1379–1384.

[4] M. Aeberhard, S. Paul, N. Kaempchen, and T. Bertram. 'Object existence probability fusion using dempster-shafer theory in a high-level sensor data fusion architecture'. In: *2011 IEEE Intelligent Vehicles Symposium (IV)*. 2011, pp. 770–775.

[5] A. Aijaz, B. Bochow, F. Dötzer, A. Festag, M. Gerlach, R. Kroh, and T. Leinmüller. 'Attacks on Inter-Vehicle Communication Systems - An Analysis'. In: *Proceedings of Workshop on Intelligent Transportation (WIT 2006)*. 2006.

[6] R. Alieiev, A. Kwoczek, and T. Hehn. 'Automotive requirements for future mobile networks'. In: *IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)*. 2015, pp. 1–4.

[7] IVHS America. *Strategic Plan for Intelligent Vehicle-highway Systems in the United States: Executive Summary*. Intelligent Vehicle Highway Society of America, 1992.

[8] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella. 'Energy conservation in wireless sensor networks: A survey'. In: *Ad Hoc Networks* 7.3 (2009), pp. 537 –568.

[9] P. Aneesh, C. Rohan, S. Rituraj, and B. Mriganka. 'Advanced Driver Assistance Systems'. In: *SAE Technical Paper*. SAE International, Feb. 2016.

[10] P. Arena, L. Fortuna, D. Lombardo, and L. Patane. 'CNN and collective perception'. In: *2008 11th International Workshop on Cellular Neural Networks and Their Applications*. IEEE. 2008, pp. 186–191.

[11] R. Balaghiasefi, M. Düring, K. Franke, and A. Zimmermann. 'Automatic fault detection and execution monitoring in cooperative maneuvering'. In: *14th International Conference on ITS Telecommunications (ITST)*. IEEE. 2015, pp. 37–44.

[12] M. Bechler, D. Heussner, T. May, I. Radusch, H. Rechner, and P. Vogel. 'simTD: a car-to-X system architecture for field operational tests'. In: *IEEE Communications Magazine* 48.5 (2010), pp. 148–154.

[13] N. Beckmann, H.-P. Kriegel, R. Schneider, and B. Seeger. *The R*-tree: an efficient and robust access method for points and rectangles*. Vol. 19. 2. ACM, 1990.

[14] A. Bensrhair, M. Bertozzi, A. Broggi, P. Miche, S. Mousset, and G. Toulminet. 'A cooperative approach to vision-based vehicle detection'. In: *IEEE Intelligent Transportation Systems*. 2001, pp. 207–212.

[15] D.P. Bertsekas. 'The auction algorithm: A distributed relaxation method for the assignment problem'. In: *Annals of operations research* 14.1 (1988), pp. 105–123.

[16] S. Blackman and R. Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House radar library. Artech House, 1999.

[17] O. Bomsel and G. Le Blanc. 'Digitalisation, innovation, and industrial organisation: the pivotal case of the auto industry'. In: *International Journal of Electronic Business* 2.2 (2004), pp. 193–204.

[18] Boost C++ Libraries. *Boost Intersect Algorithm*. 2016.

[19] J. Bortz. *Statistik: Für Human-und Sozialwissenschaftler*. Springer-Verlag, 2006.

[20] M. Broy. 'Challenges in automotive software engineering'. In: *Proceedings of the 28th international conference on Software engineering*. ACM. 2006, pp. 33–42.

[21] T. Buburuzan et al. *C2C-CC Basic System Profile*. Version 1.1.0. CAR 2 CAR Communication Consortium, Dec. 2015.

[22] B. Buchli, F. Sutton, and J. Beutel. 'GPS-Equipped Wireless Sensor Network Node for High-Accuracy Positioning Applications'. In: *Wireless Sensor Networks*. Vol. 7158. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2012, pp. 179–195.

[23] Statistisches Bundesamt. *Unfallentwicklung auf Deutschen Strassen 2015*. Wiesbaden: Statistisches Bundesamt, July 2016.

[24] W. Burghout, H. Koutsopoulos, and I. Andreasson. 'Hybrid mesoscopic-microscopic traffic simulation'. In: *Transportation Research Record: Journal of the Transportation Research Board* 1934 (2005), pp. 218–255.

[25] *C2C-CC Distributed Congestion Control (DCC) for Day One*. Version 1.0. CAR 2 CAR Communication Consortium, Dec. 2013.

[26] Car to Car Communikation Consortium. *Car to Car Communication Consortium Manifesto*. Version 1.1. Aug. 2007.

[27] Car to Car Communikation Consortium. *Memorandum of Understanding*. Europa, 2011.

[28] IPG CarMaker. *IPG driver user manual 6.4*. 2014.

[29] J. Casas, J. L. Ferrer, D. Garcia, J. Perarnau, and A. Torday. 'Traffic simulation with AIMSUM'. In: *Fundamentals of Traffic Simulation*. Springer, 2010, pp. 173–232.

[30] Z. Chaczko, F. Ahmad, and V. Mahadevarr. 'Wireless sensors in network based collaborative environments'. In: *6th International Conference on Information Technology Based Higher Education and Training (ITHET)*. 2005, F3A/7–F3A/13.

[31] G. Challita, S. Mousset, F. Nashashibi, and A. Bensrhair. 'An application of V2V communications : Cooperation of vehicles for a better car tracking using GPS and vision systems'. In: *IEEE Vehicular Networking Conference (VNC)*. 2009, pp. 1–6.

[32] C. Y. Chan. 'Connected vehicles in a connected world'. In: *International Symposium on VLSI Design, Automation and Test (VLSI-DAT)*. 2011, pp. 1–4.

[33] H. Chen, T. Kirubarajan, and Y. Bar-Shalom. 'Performance limits of track-to-track fusion versus centralized estimation: theory and application'. In: *IEEE Transactions on Aerospace and Electronic Systems* 39.2 (2003), pp. 386–400.

[34] Q. Chen, F. Schmidt-Eisenlohr, D. Jiang, M. Torrent-Moreno, L. Delgrossi, and H. Hartenstein. 'Overhaul of IEEE 802.11 modeling and simulation in ns-2'. In: *Proceedings of the 10th ACM Symposium on Modeling, analysis, and simulation of wireless and mobile systems*. ACM. 2007, pp. 159–168.

[35] D. R. Choffnes and F. E. Bustamante. 'An integrated mobility and traffic model for vehicular wireless networks'. In: *Proceedings of the 2nd ACM international workshop on Vehicular ad hoc networks*. ACM. 2005, pp. 69–78.

[36] H. Choi and H. Varian. 'Predicting the present with Google Trends'. In: *Economic Record* 88.s1 (2012), pp. 2–9.

[37] S. Choi, F. Thalmayr, D. Wee, and F. Weig. *Advanced driver-assistance systems: Challenges and opportunities ahead [Accessed: 09/10/2016]*. Oct. 2016. URL: `http://www.mckinsey.com/industries/semiconductors/our-insights/advanced-driver-assistance-systems-challenges-and-opportunities-ahead`.

[38] W. Dargie and C. Poellabauer. 'Fundamentals of Wireless Sensor Networks'. In: *A John Wiley and Sons, Ltd., Publication* (2010).

[39] A. De La Fortelle, X. Qian, S. Diemer, J. Grégoire, F. Moutarde, S. Bonnabel, A. Marjovi, A. Martinoli, I. Llatser, A. Festag, et al. 'Network of automated vehicles: the AutoNet 2030 vision'. In: *ITS World Congress*. 2014.

[40] Delphi Automotive LLP. *Delphi Electronically Scanning Radar Datasheet*.

[41] K. Dietmayer, A. Kirchner, and N. Kämpchen. 'Fusionsarchitekturen zur Umfeldwahrnehmung für zukünftige Fahrerassistenzsysteme'. In: *Fahrerassistenzsysteme mit maschineller Wahrnehmung*. Springer, 2005, pp. 59–88.

[42] *DIN ISO 8855: Road vehicles - Vehicle dynamics and road-holding ability - Vocabulary*. DIN, Nov. 2013.

[43] P. Dollar, C. Wojek, B. Schiele, and P. Perona. 'Pedestrian detection: An evaluation of the state of the art'. In: *IEEE transactions on pattern analysis and machine intelligence* 34.4 (2012), pp. 743–761.

[44] US DOT. *Intelligent Transporation Systems Joint Program Office [Accessed: 09/10/2016]*. Sept. 2016. URL: `http://www.its.dot.gov/history/index.html`.

[45] O. Dubuisson. *ASN. 1: communication between heterogeneous systems*. M. Kaufmann, 2001.

[46] M. Düring and P. Pascheka. 'Cooperative decentralized decision making for conflict resolution among autonomous agents'. In: *IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA)*. 2014, pp. 154–161.

[47] D. Eckhoff, N. Sofra, and R. German. 'A Performance Study of Cooperative Awareness in ETSI ITS G5 and IEEE WAVE'. In: *10th Annual Conference on Wireless On-Demand Network Systems and Services (WONS)*. 2013.

[48] D. Eckhoff, N. Sofra, and R. German. 'A performance study of cooperative awareness in ETSI ITS G5 and IEEE WAVE'. In: *10th Annual Conference onWireless On-demand Network Systems and Services (WONS)*. Mar. 2013, pp. 196–200.

[49] D. Eckhoff, C. Sommer, and F. Dressler. 'On the Necessity of Accurate IEEE 802.11p Models for IVC Protocol Simulation'. In: *75th IEEE Vehicular Technology Conference (VTC2012-Spring)*. Yokohama, Japan: IEEE, 2012, pp. 1–5.

[50] N. Economides and C. Himmelberg. 'Critical mass and network evolution in telecommunications'. In: *Toward a competitive telecommunications industry: Selected papers from the 1994 telecommunications policy research conference*. 1995, pp. 47–63.

[51] S. Eichler. 'Performance evaluation of the IEEE 802.11 p WAVE communication standard'. In: *IEEE 66th Vehicular Technology Conference*. IEEE. 2007, pp. 2199–2203.

[52] *ETSI EN 302 636-1 V1.2.0 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 1: Requirements*. ETSI, Aug. 2013.

[53] *ETSI EN 302 636-2 V1.2.1 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 2: Scenarios*. ETSI, Nov. 2013.

[54] *ETSI EN 302 636-3 V1.2.1 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 2: Network Architecture*. ETSI, Dec. 2014.

[55] *ETSI EN 302 636-4-1 V1.2.0 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 4: Geographical addressing and forwarding for point-to-point and point-to-multipoint communications; Sub-part 1: Media-Independent Functionality (Draft)*. ETSI, Oct. 2013.

[56] *ETSI EN 302 636-5-1 V1.2.0 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 5: Transport Protocols; Sub-part 1: Basic Transport Protocol (Draft)*. ETSI, Oct. 2013.

[57] *ETSI EN 302 637-2 V1.3.2 - Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 2: Specification of Cooperative Awareness Basic Service*. ETSI, Nov. 2014.

[58] *ETSI EN 302 637-3 V1.2.2 - Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 3: Specifications of Decentralized Environmental Notification Basic Service*. ETSI, Sept. 2014.

[59] *ETSI EN 302 664 V1.2.1 - Intelligent Transport Systems (ITS); Access layer specification for Intelligent Transport Systems operating in the 5 GHz frequency band*. ETSI, Nov. 2014.

[60] *ETSI EN 302 665 V1.1.1 - Intelligent Transport Systems; Communications Architecture.* ETSI, Sept. 2010.

[61] *ETSI EN 302 895V1.0.0 - Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Local Dynamic Map.* ETSI, Jan. 2014.

[62] *ETSI Intelligent Transport Systems Group [Accessed: 09/10/2016].* Oct. 2016. URL: `http://www.etsi.org/technologies-clusters/technologies/intelligent-transport`.

[63] *ETSI TR 101 112 V3.1.0 - Universal Mobile Telecommunications System (UMTS); Selection procedures for the choice of radio transmission technologies of the UMTS (UMTS 30.03 version 3.1.0).* ETSI, Nov. 1997.

[64] *ETSI TR 101 612 V1.1.1 - Intelligent Transport Systems; Cross Layer DCC Management Entity for operation in the ITS G5A and ITS G5B medium; Report on Cross layer DCC algorithms and performance evaluation.* ETSI, Sept. 2014.

[65] *ETSI TR 102 893 V1.1.1 - Intelligent Transport Systems; Security; Threat, Vulnerability and Risk Analysis (TVRA).* ETSI, Mar. 2010.

[66] *ETSI TS 101 539-1 V1.1.1 - Intelligent Transport Systems (ITS);V2X Applications; Part 1: Road Hazard Signalling (RHS) appliation requirements specification.* ETSI, Aug. 2013.

[67] *ETSI TS 101 539-2 V1.1.1 - Intelligent Transport Systems (ITS);V2X Applications; Part 2: Intersection Collision Risk Warning (ICRW) appliation requirements specification.* ETSI, Nov. 2013.

[68] *ETSI TS 101 539-3 V1.1.1 - Intelligent Transport Systems (ITS);V2X Applications; Part 3: Road Longitudinal Collision Risk Warning (LCRW) appliation requirements specification.* ETSI, Nov. 2013.

[69] *ETSI TS 102 097 V1.2.1 - Intelligent Transport Systems; Security; Security header and certificate formats.* ETSI, June 2015.

[70] *ETSI TS 102 636-4-2 V1.1.1 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 4: Geographical addressing and forwarding for point-to-point and point-to-multipoint communications; Sub-part 2: Media-dependent functionalities for ITS-G5.* ETSI, Oct. 2013.

[71] *ETSI TS 102 636-6-1 V1.1.1 - Intelligent Transport Systems (ITS); Vehicular Communications; GeoNetworking; Part 6: Internet Integration; Sub-part 1: Transmission of IPv6 Packets over GeoNetworking Protocols.* ETSI, Mar. 2011.

[72] *ETSI TS 102 637-1 V1.1.1 - Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 1: Functional Requirements.* ETSI, Sept. 2010.

[73] *ETSI TS 102 687 V1.1.1 - Intelligent Transport Systems (ITS); Decentralized Congestion Control Mechanisms for Intelligent Transport Systems operating in the 5 GHz frequency band.* ETSI, Oct. 2012.

[74] *ETSI TS 102 723-2 V1.1.1 - Intelligent Transport Systems; OSI cross-layer-topics; Part 2: Management information base.* ETSI, Nov. 2012.

[75] *ETSI TS 102 723-3 V1.1.1 - Intelligent Transport Systems; OSI cross-layer-topics; Part 3: Interface between management entity and access layer*. ETSI, Nov. 2012.

[76] *ETSI TS 102 723-4 V1.1.1 - Intelligent Transport Systems; OSI cross-layer-topics; Part 4: Interface between management entity and networking & transport layer*. ETSI, Nov. 2012.

[77] *ETSI TS 102 723-5 V1.1.1 - Intelligent Transport Systems; OSI cross-layer-topics; Part 5: Interface between management entity and facilities layer*. ETSI, Nov. 2012.

[78] *ETSI TS 102 723-8 V1.1.1 - Intelligent Transport Systems; OSI cross-layer-topics; Part 8: Interface between security entity and network and transport layer*. ETSI, Apr. 2016.

[79] *ETSI TS 102 724 V1.1.1 - Intelligent Transport Systems (ITS); Harmonized Channel Specifications for Intelligent Transport Systems operating in the 5 GHz frequency band*. ETSI, Oct. 2012.

[80] *ETSI TS 102 731 V1.1.1 - Intelligent Transport Systems; Security; Security Services and Architecture*. ETSI, Sept. 2010.

[81] *ETSI TS 102 867 V1.1.1 - Intelligent Transport Systems; Security; Stage 3 mapping for IEEE 1609.2*. ETSI, June 2012.

[82] *ETSI TS 102 894-1 V1.1.1 - Intelligent Transport Systems; Users and applications requirements; Part 1: Facility layer structure, functional requirements and specifications*. ETSI, Sept. 2010.

[83] *ETSI TS 102 894-2 V1.2.1 - Intelligent Transport Systems (ITS); Users and applications requirements; Part 2: Applications and facilities layer common data dictionary*. ETSI, Sept. 2014.

[84] *ETSI TS 102 940 V1.1.1 - Intelligent Transport Systems; Security; ITS communications security architecture and security management*. ETSI, June 2012.

[85] *ETSI TS 102 941 V1.1.1 - Intelligent Transport Systems; Security; Trust and Privacy Management*. ETSI, June 2012.

[86] *ETSI TS 102 942 V1.1.1 - Intelligent Transport Systems; Security; Access Control*. ETSI, June 2012.

[87] *ETSI TS 102 943 V1.1.1 - Intelligent Transport Systems; Security; Confidentiality services*. ETSI, June 2012.

[88] *ETSI TS 103 175 V1.1.1 - Intelligent Transport Systems; Cross Layer DCC Management Entity for operation in the ITS G5A and ITS G5B medium*. ETSI, June 2015.

[89] European Commission. 'Commission Decision 2008/671/EC of 5 August 2008 on the harmonised use of radio spectrum in the 5 875-5 905 MHz frequency band for safety-related applications of Intelligent Transport Systems (ITS)'. In: (2008).

[90] European Commission. *M/453 - Standardisation Mandate addressed to CEN and ETSI in the field of information and communication technologies to support the interoperability of co-operative systems for intelligent transport in the European Community*. 2009.

[91] K. Fanyu and T. Jindong. 'A collaboration-based hybrid vehicular sensor network architecture'. In: *International Conference on Information and Automation (ICIA 2008)*. 2008, pp. 584–589.

[92] L. Figueiredo, I. Jesus, J. T. Machado, J. Ferreira, and J.L. Martins de Carvalho. 'Towards the development of intelligent transportation systems'. In: *Intelligent transportation systems*. Vol. 88. 2001, pp. 1206–1211.

[93] A. Filippi, K. Moerman, G. Daalderop, P. D. Alexander, F. Schober, and W. Pfliegl. *Ready to roll: Why 802.11p beats LTE and 5G for V2x [Accessed: 05.02.2017]*. 2016. URL: http://www.automotive-eetimes.com/design-center/why-80211p-beats-lte-and-5g-v2x.

[94] K. Franke, R. Balaghiasefi, M. Düring, and H.-J. Günther. 'A Cooperative Driver Assistance System: Decentralization Process and Test Framework'. In: *7. Tagung Fahrerassistenzsysteme*. 2015.

[95] K. Franke, M. Düring, R. Balaghiasefi, M. Gonter, K. Lemmer, and F. Küçükay. 'A Reference Architecture for CISS/CDAS within the Field of Cooperative Driving'. In: *3rd International Conference on Connected Vehicles and Expo, Vienna*. 2014.

[96] K. Franke, M. Gonter, A. Leschke, and F. Küçükay. 'Steigerung der Fahrzeugsicherheit durch Car2X-Kommunikation'. In: *Automobiltechnische Zeitschrift* 114.11 (2012).

[97] R. L. French. *IEEE'S newest entity focuses on solving transportation problems worldwide*. 1998.

[98] M. Fukushima. 'The latest trend of v2x driver assistance systems in Japan'. In: *Computer Networks* 55 (2011), pp. 3134–3141.

[99] P. Furgale, U. Schwesinger, M. Rufli, W. Derendarz, H. Grimmett, P. Muehlfellner, S. Wonneberger, J. Timpner, S. Rottmann, B. Li, et al. 'Toward automated driving in cities using close-to-market sensors: An overview of the V-charge project'. In: *Intelligent Vehicles Symposium (IV)*. IEEE. 2013, pp. 809–816.

[100] P. Gao, H. Russell, and A. Zielke. 'A road map to the future for the auto industry'. In: *McKinsey Quarterly* (2014).

[101] P. Gao, H.-W. Kaas, D. Mohr, and D. Wee. 'Disruptive trends that will transform the auto industry'. In: *McKinsey Report* (2016).

[102] VIRES Simulationstechnologie GmbH. *Vires Virtual Test Drive [Accessed: 31.12.2016]*. URL: https://www.vires.com/docs/VIRES_VTD_Details_201403.pdf.

[103] A. Gorji, M. B. Menhaj, and S. Shiry. 'Multiple target tracking for mobile robots using the JPDAF algorithm'. In: *Tools and Applications with Artificial Intelligence*. Springer, 2009, pp. 51–68.

[104] H.-J. Günther, R. Riebl, L. Wolf, and C. Facchi. 'Collective perception and decentralized congestion control in vehicular ad-hoc networks'. In: *2016 IEEE Vehicular Networking Conference (VNC)*. 2016, pp. 1–8.

[105] H.-J. Günther, J. Timpner, M. Wegner, R. Riebl, and L. Wolf. 'Extending a holistic microscopic IVC simulation environment with local perception sensors and LTE capabilities'. In: *Vehicular Communications* (2017).

[106] H.-J. Günther, S. Kleinau, O. Trauer, and L. Wolf. 'Platooning at traffic lights'. In: *2016 IEEE Intelligent Vehicles Symposium (IV)*. 2016, pp. 1047–1053.

[107] H.-J. Günther, B. Mennenga, O. Trauer, R. Riebl, and L. Wolf. 'Realizing collective perception in a vehicle'. In: *2016 IEEE Vehicular Networking Conference (VNC)*. 2016, pp. 1–8.

[108] H.-J. Günther, O. Trauer, and L. Wolf. 'The Potential of Collective Perception in Vehicular Ad-hoc Networks'. In: *14th IEEE International Conference on ITS Telecommunications (ITST)*. 2015.

[109] P. Hank, S. Müller, O. Vermesan, and J. Van Den Keybus. 'Automotive ethernet: in-vehicle networking and smart mobility'. In: *Proceedings of the Conference on Design, Automation and Test in Europe*. EDA Consortium. 2013, pp. 1735–1739.

[110] L. Hao and F. Nashashibi. 'Multi-vehicle cooperative perception and augmented reality for driver assistance: A possibility to see through front vehicle'. In: *14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. 2011, pp. 242–247.

[111] G. Held. *Inter- and Intra-Vehicle Communications*. Auerbach Publishers Inc., 2007.

[112] F. R. Helmert. *Mathematical and Physical Theories of Higher Geodesy, Part 1, Preface and the Mathematical Theories*. Scan by Charles Karney of the copy in the USGS library in Reston, VA. The translation is a work of the U.S. Government and so is in the public domain. 1964.

[113] T. R. Henderson, M. Lacage, G. F. Riley, C. Dowell, and J. Kopena. 'Network simulations with the ns-3 simulator'. In: *SIGCOMM demonstration* 15 (2008), p. 17.

[114] L. Hobert. 'Autonet 2030 - Specifications for the enhancement to existing LDM and cooperative communication protocol standards'. In: *Autonet 2030 Deliverable 3.2*. 2015.

[115] L. Hobert, A. Festag, I. Llatser, L. Altomare, F. Visintainer, and A. Kovacs. 'Enhancements of V2X communication in support of cooperative autonomous driving'. In: *IEEE Communications Magazine* 53.12 (2015), pp. 64–70.

[116] K. Homeier and L. Wolf. 'RoadGraph: High level sensor data fusion between objects and street network'. In: *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE. 2011, pp. 1380–1385.

[117] N. Höver, B. Lichte, and S. Lietaert. *Multi-beam Lidar sensor for active safety applications*. Tech. rep. SAE Technical Paper, 2006.

[118] T.-Y. Hsieh and C.-W. Hsu. 'Cooperative vehicular information collection based on the cell-weighted policy'. In: *12th International Conference on ITS Telecommunications (ITST)*. 2012, pp. 195–198.

[119] J.-P. Hubaux, S. Capkun, and J. Luo. 'The security and privacy of smart vehicles'. In: *IEEE Security and Privacy Magazine* 2.LCA-ARTICLE-2004-007 (2004), pp. 49–55.

[120] D. Hübner, ed. *PROMETHEUS Phase II:PRO-COM, Final Report TV 8927*. Aachen: RWTH Aachen, Lehrstuhl für Informatik 4, 1993.

[121] ibeo Automotive Systems GmbH. *The ibeo LUX sensor family datasheet [Accessed: 05/03/2017]*. http://www.autonomoustuff.com/wp-content/uploads/2016/07/Lux-Family-Data-Sheet.pdf.

[122] *IEEE Std 802 - 2001, Standard for Local and Metropolitan Area Networks: Overview and Architecture*. IEEE Computer Society, 2001.

[123] *IEEE Std 802.11-2012, Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*. IEEE Computer Society, Mar. 2012.

[124] *IEEE Std 802.2, Information technology - Telecommunications and information exchange between systems - Local and metropolitan area networks - Specific requirements - Part 2: Logical Link Control*. IEEE Computer Society, 1998.

[125] Bundesministerium für Verkehr und digitale Infrastruktur. *Verkehrssicherheitsprogramm 2011*. Berlin: Bundesministerium für Verkehr und digitale Infrastruktur, 2011.

[126] *J2735 - Surface Vehicle Standard, Dedicated Short Range Communications (DSRC) Message Set Dictionary*. SAE International, Jan. 2016.

[127] C. Jennings, D. Murray, and J.J. Little. 'Cooperative robot localization with vision-based mapping'. In: *International Conference on Robotics and Automation*. Vol. 4. 1999, 2659–2665 vol.4.

[128] V. Johanning and R. Mildner. *Car IT kompakt - Das Auto der Zukunft - Vernetzt und autonom fahrend*. Springer Fachmedien Wiesbaden, 2015.

[129] R. A. Johnson, D. W. Wichern, et al. *Applied multivariate statistical analysis*. Vol. 5. 8. Prentice hall Upper Saddle River, NJ, 2002.

[130] A. Josang. 'Artificial Reasoning with Subjective Logic'. In: *Proceedings of the second Australian workshop on commonsense reasoning*. 48. 1997.

[131] W. Kang, K. Kapitanova, and S. H. Son. 'RDDS: A real-time data distribution service for cyber-physical systems'. In: *IEEE Transactions on Industrial Informatics* 8.2 (2012), pp. 393–405.

[132] C. F. F. Karney. 'Algorithms for geodesics'. In: *Journal of Geodesy* 87.1 (2013), pp. 43–55.

[133] L. Kelch, T. Pögel, L. Wolf, and A. Sasse. 'CQI Maps for Optimized Data Distribution'. In: *Vehicular Technology Conference (VTC Fall), 2013 IEEE 78th*. IEEE. 2013, pp. 1–5.

[134] Y. B. Ko and N. H. Vaidya. 'Flooding-based geocasting protocols for mobile ad hoc networks'. In: *Mobile Networks and Applications* 7.6 (2002), pp. 471–480.

[135] J. Korhonen and Y. Wang. 'Effect of packet size on loss rate and delay in wireless links'. In: *IEEE Wireless Communications and Networking Conference, 2005*. Vol. 3. IEEE. 2005, pp. 1608–1613.

[136] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker. 'Recent Development and Applications of SUMO - Simulation of Urban MObility'. In: *International Journal On Advances in Systems and Measurements* 5.3&4 (Dec. 2012), pp. 128–138.

[137] D. Krajzewicz, G. Hertkorn, C. Rössel, and P. Wagner. 'SUMO (Simulation of Urban MObility)-an open-source traffic simulation'. In: *Proceedings of the 4th Middle East Symposium on Simulation and Modelling (MESM20002)*. 2002, pp. 183–187.

[138] U. Kulau, S. Schildt, S. Rottmann, B. Gernert, and L. Wolf. 'PotatoNet – Outdoor WSN Testbed for Smart Farming Applications'. In: *Proceedings of the 14th GI/ITG KuVS Fachgespräch Drahtlose Sensornetze Ulm*. FGSN15 (2015).

[139] J. Larmouth. *ASN. 1 complete*. M. Kaufmann, 2000.

[140] N. Lensing. *Straßenverkehrszählung 2010: Ergebnisse (V 233)*. Bundesanstalt für Straßenwesen, 2013.

[141] I. Leontiadis, C. Efstratiou, C. Mascolo, and J. Crowcroft. 'SenShare: Transforming Sensor Networks into Multi-application Sensing Infrastructures'. In: *Wireless Sensor Networks*. Vol. 7158. Lecture Notes in Computer Science. Springer, 2012, pp. 65–81.

[142] J. Levinson, J. Askeland, J. Becker, J. Dolson, D. Held, S. Kammel, J. Z. Kolter, O. Langer D. Pink, V. Pratt, et al. 'Towards fully autonomous driving: Systems and algorithms'. In: *2011 IEEE Intelligent Vehicles Symposium (IV)*. IEEE. 2011, pp. 163–168.

[143] X. R. Li and V. P. Jilkov. 'Survey of maneuvering target tracking. Part I. Dynamic models'. In: *IEEE Transactions on aerospace and electronic systems* 39.4 (2003), pp. 1333–1364.

[144] S. J. Liebowitz and S. E. Margolis. 'Network externality: An uncommon tragedy'. In: *The Journal of Economic Perspectives* 8.2 (1994), pp. 133–150.

[145] W. Liu, S.W. Kim, Z.J. Chong, X.T. Shen, and M.H. Ang. 'Motion planning using cooperative perception on urban road'. In: *6th IEEE Conference on Robotics, Automation and Mechatronics (RAM)*. 2013, pp. 130–137.

[146] I. Loevsky and I. Shimshoni. 'Reliable and efficient landmark-based localization for mobile robots'. In: *Robotics and Autonomous Systems* 58.5 (2010), pp. 520–528.

[147] N. Lu, N. Cheng, N. Zhang, X. Shen, and J. W. Mark. 'Connected vehicles: Solutions and challenges'. In: *IEEE internet of things journal* 1.4 (2014), pp. 289–299.

[148] B. Lucas, R. Held, G.-P. Duba, M. Maurer, M. Klar, and D. Freundt. 'Frontsensorsystem mit Doppel Long Range Radar'. In: *5. Workshop Fahrerassistenzsysteme, Walting*. 2008.

[149] O. Maibaum and S. Rebeschieß. 'Test von adaptiven Softwaremechanismen zur Fehlerkompensation'. In: *Simulation und Test in der Funktions-und Softwareentwicklung für die Automobilelektronik* 45 (2005), pp. 179–186.

[150] F. J. Martinez, C. K. Toh, J.-C. Cano, C. T. Calafate, and P. Manzoni. 'A survey and comparative study of simulators for vehicular ad hoc networks (VANETs)'. In: *Wireless Communications and Mobile Computing* 11.7 (2011), pp. 813–828.

[151] K. Matheus, R. Morich, and L. Andreas. 'Economic background of car-to-car communication'. In: *Proceedings of the 2. Braunschweiger Symposium Informationssysteme für mobile Anwendungen. Braunschweig.* 2004.

[152] I.V. Melnyk, J.A. Hesch, and S.I. Roumeliotis. 'Cooperative vision-aided inertial navigation using overlapping views'. In: *International Conference on Robotics and Automation (ICRA).* 2012, pp. 936–943.

[153] C. Merfels and C. Stachniss. 'Pose fusion with chain pose graphs for automated driving'. In: *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* IEEE. 2016, pp. 3116–3123.

[154] L. Merino, F. Caballero, J.R. Martinez-de Dios, J. Ferruz, and A. Ollero. 'A Cooperative Perception System for Multiple UAVs: Application to Automatic Detection of Forest Fires'. In: *Field Robotics* (2006).

[155] L. Merino, R. Rafael Martinez, and R. Anibal Ollero. 'Cooperative perception for fire monitoring'. In: *World Automation Congress.* Vol. 15. 2004, pp. 435–440.

[156] S. Messelodi, M. Modena Carla, M. Zanin, F. G. B. De Natale, F. Granelli, E. Betterle, and A. Guarise. 'Intelligent extended floating car data collection'. In: *Expert systems with Applications* 36.3 (2009), pp. 4213–4227.

[157] T. Meuser, P. Lieser, T.A.B. Nguyen, D. Böhnstedt, and R. Steinmetz. 'Adaptive Information Aggregation for Application-specific Demands'. In: (accepted for publication), 2017.

[158] Z. H. Mir and F. Filali. 'Simulation and Performance Evaluation of Vehicle-to-Vehicle (V2V) Propagation Model in Urban Environment'. In: *7th IEEE International Conference on Intelligent Systems, Modelling and Simulation.* 2016.

[159] J. A. Misener, Subir B., and G. Larson. 'Development of V-to-X systems in North America: The promise, the pitfalls and the prognosis'. In: *Computer Networks* 55 (2011), pp. 3120–3133.

[160] M. Munz, K. Dietmayer, and M. Malhlisch. 'A sensor independent probabilistic fusion system for driver assistance systems'. In: *12th International IEEE Conference on Intelligent Transportation Systems (ITSC 2009).* 2009, pp. 1–6.

[161] W. G: Najm, J. Koopmann, J. D. Smith, and J. Brewer. *Frequency of target crashes for intellidrive safety systems.* Tech. rep. US National Highway Traffic Safety Adminitration, 2010.

[162] W. Niemeier. *Ausgleichungsrechnung: statistische Auswertemethoden.* De Gruyter Lehrbuch. De Gruyter, 2008.

[163] NIMA / Geodesy and Geophysiscs Department. *Department of Defense World Geodetic System 1984.* National Imagery and Mapping Agency (NIMA), 2000.

[164] T. Nothdurft, P. Hecker, S. Ohl, F. Saust, M. Maurer, A. Reschka, and J. R. Böhmer. 'Stadtpilot: First fully autonomous test drives in urban traffic'. In: *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE. 2011, pp. 919–924.

[165] M. Obst, L. Hobert, and P. Reisdorf. 'Multi-sensor data fusion for checking plausibility of V2V communications by vision-based multiple-object tracking'. In: *2014 IEEE Vehicular Networking Conference (VNC)*. IEEE. 2014, pp. 143–150.

[166] C. Okoli and K Schabram. 'A Guide to Conducting a Systematic Literature Review of Information Systems Research'. In: *Sprouts: Working Papers on Information Systems* 10.26 (2010).

[167] C. Olivier and O. Dessoude. 'Heterogeneous sensors cooperation for an advanced perception system'. In: *Fifth International Conference on Advanced Robotics - Robots in Unstructured Environments (ICAR)*. Vol. 2. 1991, pp. 1275–1280.

[168] Oxford Technical Solutions. *RT3000 Data Sheet*. Tech. rep. 2016.

[169] L.G. Papaleondiou and M.D. Dikaiakos. 'TrafficModeler: A Graphical Tool for Programming Microscopic Traffic Simulators through High-Level Abstractions'. In: *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*. 2009, pp. 1–5.

[170] P. Pascheka and M. Düring. 'Advanced cooperative decentralized decision making using a cooperative reward system'. In: *International Symposium on Innovations in Intelligent SysTems and Applications (INISTA)*. IEEE. 2015, pp. 1–7.

[171] Forschungsinitiative Ko-FAS Verbundprojekt Ko PER. 'Ko-PER spezifische Nachrichteninhalte ASN1 Spezifikation (öffentliche Fassung) μMS 2.720-2'. In: *Ko-FAS Deliverables* (2012).

[172] W. Pietzsch and G. Wolf. *Straßenplanung*. Werner-Ingenieur-Texte. 2000.

[173] F. de Ponte Müller, E.M. Diaz, B. Kloiber, and T. Strang. 'Bayesian cooperative relative vehicle positioning using pseudorange differences'. In: *2014 IEEE/ION Position, Location and Navigation Symposium-PLANS 2014*. IEEE. 2014, pp. 434–444.

[174] F. de Ponte Müller, E. M. Diaz, and I. Rashdan. 'Cooperative positioning and radar sensor fusion for relative localization of vehicles'. In: *Intelligent Vehicles Symposium (IV), 2016 IEEE*. IEEE. 2016, pp. 1060–1065.

[175] R. Popescu-Zeletin, I. Radusch, and M.-A. Rigani. *Vehicular-2-X communication: state-of-the-art and research in mobile vehicular ad hoc networks*. Springer Science & Business Media, 2010.

[176] D. Rabel. 'Basis der Automatisierung Präzise, dynamische Echtzeitkarten und menschliches Fahrverhalten'. In: *ATZelektronik* 11.4 (2016), pp. 44–49.

[177] R. Rasshofer and K. Gresser. 'Automotive radar and lidar systems for next generation driver assistance functions'. In: *Advances in Radio Science* 3.B. 4 (2005), pp. 205–209.

[178] A. Rauch, F. Klanner, and K. Dietmayer. 'Analysis of V2X communication parameters for the development of a fusion architecture for cooperative perception systems'. In: *IEEE Intelligent Vehicles Symposium (IV)*. June 2012, pp. 685–690.

[179] A. Rauch, F. Klanner, R. Rasshofer, and K. Dietmayer. 'Car2X-Based Perception in a High-Level Fusion Architecture for Cooperative Perception Systems'. In: *IEEE Intelligent Vehicles Symposium (IV)*. June 2011, pp. 270–275.

[180] A. Rauch, S. Maier, F. Klanner, and K. Dietmayer. 'Inter-vehicle object association for cooperative perception systems'. In: *16th International IEEE Conference on Intelligent Transportation Systems - (ITSC)*. Oct. 2013, pp. 893–898.

[181] M. Raya and J.-P. Hubaux. 'Securing vehicular ad hoc networks'. In: *Journal of Computer Security* 15.1 (2007), pp. 39–68.

[182] M. Reiss, B. Sick, and M. Strassberger. 'Collaborative Situation-Awareness in Vehicles by Means of Spatio-Temporal Information Fusion With Probabilistic Networks'. In: *IEEE Mountain Workshop on Adaptive and Learning Systems*. 2006, pp. 189–194.

[183] R. Riebl, H.-J. Günther, C. Facchi, and L. Wolf. 'Artery - Extendig Veins for VANET applications'. In: *Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. 2015.

[184] R. Riebl and C. Facchi. 'Implementation of Day One ITS-G5 Systems for Testing Purposes'. In: *Proceedings of the 2nd GI/ITG KuVS Fachgespräch Inter-Vehicle Commuication Luxembourg (FG-IVC 2014)*. Feb. 2014, pp. 33–36.

[185] R. Riebl, M. Monz, S. Varga, L. Maglaras, H. Janicke, A. H. Al-Bayatti, and C. Facchi. 'Improved security performance for vanet simulations'. In: *IFAC-PapersOnLine* 49.30 (2016), pp. 233–238.

[186] R. Riebl and C. Facchi. 'Regain Control of Growing Dependencies in OMNeT++ Simulations'. In: *arXiv preprint arXiv:1509.03561* (2015).

[187] R: Riebl, C. Obermaier, S. Neumeier, and C. Facchi. 'Vanetza: Boosting Research on Inter-Vehicle Communication'. In: *5th GI/ITG KuVS Fachgespräch Inter-Vehicle Communication Erlangen* (2017), p. 37.

[188] Robert Bosch GmbH. *Chassis Systems Control - LRR3: 3rd generation Long-Range Radar Sensor*. Chassis Systems Control Driver Assistance.

[189] I. Rodriguez, E. P.L. Almeida, M. Lauridsen, D. A. Wassie, L. C. Gimenez, H. C. Nguyen, T. B. Srensen, and P. Mogensen. 'Measurement-based Evaluation of the Impact of Large Vehicle Shadowing on V2X Communications'. In: *Proceedings of 22nd European Wireless Conference*. VDE Verlag GMBH. 2016.

[190] M. Rondinone, J. Maneros, D. Krajzewicz, R. Bauza, P. Cataldi, F. Hrizi, J. Gozalvez, V. Kumar, M. Röckl, L. Lin, et al. 'iTETRIS: a modular simulation platform for the large scale evaluation of cooperative ITS applications'. In: *Simulation Modelling Practice and Theory* 34 (2013), pp. 99–125.

[191] A. Rostami, B. Cheng, G. Bansal, K. Sjoberg, M. Gruteser, and J. B. Kenney. 'Stability Challenges and Enhancements for Vehicular Channel Congestion Control Approaches'. In: *IEEE Transactions on Intelligent Transportation Systems* PP.99 (2016), pp. 1–14.

[192] O. Scharfenberg. *Telekommunikations- und Automobilunternehmen gründen globale branchenübergreifende 5G Automotive Association [Accessed: 12/10/2016]*. URL: https://www.audi-mediacenter.com/de/pressemitteilungen/telekommunikations-und-automobilunternehmen-gruenden-globale-branchenuebergreifende-5g-automotive-association-6817.

[193] T. Schmickl, C. Möslinger, and K. Crailsheim. 'Collective Perception in a Robot Swarm'. In: *Swarm Robotics Workshop*. Vol. 4433. LNCS. Springer, 2007, pp. 144–157.

[194] H. Schumacher, H. Tchouankem, J. Nuckelt, T. Kürner, T. Zinchenko, A. Leschke, and L. Wolf. 'Vehicle-to-Vehicle IEEE 802.11 p performance measurements at urban intersections'. In: *2012 IEEE International Conference on Communications (ICC)*. IEEE. 2012, pp. 7131–7135.

[195] B. Schünemann. 'The V2X Simulation Runtime Infrastructure: VSimRTI'. In: *Doctor of Philosopy, Mathematics and Natural Sciences University at Potsdam, Germany* (2011).

[196] F. Seeliger, G. Weidl, D. Petrich, F. Naujoks, G. Breuel, A. Neukum, and K. Dietmayer. 'Advisory warnings based on cooperative perception'. In: *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*. 2014, pp. 246–252.

[197] M. A. Shah and N. Aouf. 'Dynamic cooperative perception and path planning for collision avoidance'. In: *6th International Symposium on Mechatronics and its Applications (ISMA 2009)*. 2009, pp. 1–7.

[198] Y. Bar Shalom. 'Multitarget-multisensor tracking: advanced applications'. In: *Norwood, MA, Artech House, 1990, 391 p.* 1 (1990).

[199] K. Sjöberg. *Medium access control for vehicular ad hoc networks*. Chalmers University of Technology, 2013.

[200] L. E. Sjöberg and M. Shirazian. 'Solving the Direct and Inverse Geodetic Problems on the Ellipsoid by Numerical Integration'. In: *Journal of Surveying Engineering* 138.1 (2012), pp. 9–16.

[201] R. Smith and P. Cheeseman. 'On the Representation and Estimation of Spatial Uncertainly'. In: *Int. J. Rob. Res.* 5.4 (1986), pp. 56–68.

[202] C. Sommer, D. Eckhoff, R. German, and F. Dressler. 'A Computationally Inexpensive Empirical Model of IEEE 802.11p Radio Shadowing in Urban Environments'. In: *Eighth International Conference on Wireless On-Demand Network Systems and Services*. Jan. 2011, pp. 84–90.

[203] C. Sommer, R. German, and F. Dressler. 'Bidirectionally Coupled Network and Road Traffic Simulation for Improved IVC Analysis'. In: *IEEE Transactions on Mobile Computing* 10.1 (2011), pp. 3–15.

[204] C. Sommer, Z. Yao, R. German, and F. Dressler. 'On the need for bidirectional coupling of road traffic microsimulation and network simulation'. In: *Proceedings of the 1st ACM SIGMOBILE workshop on Mobility models*. ACM. 2008, pp. 41–48.

[205] C. Sommer and F. Dressler. 'Progressing Toward Realistic Mobility Models in VANET Simulations'. In: *IEEE Communications Magazine* 46.11 (2008), pp. 132–137.

[206] C. Sommer, I. Dietrich, and F. Dressler. 'Realistic Simulation of Network Protocols in VANET Scenarios'. In: *26th IEEE Conference on Computer Communications (INFOCOM 2007): IEEE Workshop on Mobile Networking for Vehicular Environments (MOVE 2007), Poster Session*. Anchorage, AK: IEEE, 2007, pp. 139–143.

[207] C. Sommer and F. Dressler. 'Using the Right Two-Ray Model? A Measurement based Evaluation of PHY Models in VANETs'. In: *17th ACM International Conference on Mobile Computing and Networking (MobiCom 2011)*. Las Vegas, NV: ACM, Sept. 2011.

[208] M.T.J. Spaan, T.S. Veiga, and P.U. Lima. 'Active cooperative perception in network robot systems using POMDPs'. In: *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 2010, pp. 4800–4805.

[209] C. Stiller, A. Bachmann, and A. Geiger. 'Maschinelles Sehen'. In: *Handbuch Fahrerassistenzsysteme*. Springer, 2015, pp. 369–393.

[210] D. Stüker. 'Heterogene Sensordatenfusion zur robusten Objektverfolgung im automobilen Straßenverkehr'. PhD thesis. Universität Oldenburg, 2004.

[211] *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems*. SAE International, Jan. 2014.

[212] H. Tchouankem, T. Zinchenko, H. Schumacher, and L. Wolf. 'Effects of Vegetation on Vehicle-to-Vehicle Communication Performance at Intersections'. In: *Vehicular Technology Conference (VTC Fall), 2013 IEEE 78th*. IEEE. 2013, pp. 1–6.

[213] M. N. Tehrani, M. Uysal, and H. Yanikomeroglu. 'Device-to-device communication in 5G cellular networks: challenges, solutions, and future directions'. In: *IEEE Communications Magazine* 52.5 (2014), pp. 86–92.

[214] J. Timpner, M. Wegner, H.-J. Günther, and L. Wolf. 'High-resolution Vehicle Telemetry via Heterogeneous IVC'. In: *Proceedings of the First International Workshop on Internet of Vehicles and Vehicles of Internet*. IoV-VoI '16. ACM, 2016, pp. 19–24.

[215] J. Timpner, M. Wegner, H.-J. Günther, and L. Wolf. 'Towards a Multi-Protocol Microscopic IVC Simulation Environment for ADASs'. In: *Fachgespräch Inter-Vehicle Communication Berlin* (2016).

[216] J. Timpner, S. Rottmann, and L. Wolf. 'Vehicular Communications in the V-Charge Project'. In: *Fachgespräch Inter-Vehicle Communication Luxembourg* (2014), p. 40.

[217] C. Tingvall and N. Haworth. 'Vision Zero: an ethical approach to safety and mobility'. In: *6th ITE International Conference Road Safety & Traffic Enforcement*. Vol. 1999. 2000.

[218] K. Tischler and B. Hummel. 'Enhanced environmental perception by inter-vehicle data exchange'. In: *IEEE Intelligent Vehicles Symposium*. 2005, pp. 313–318.

[219] K. Tischler, M. Clauss, Y. Guenter, N. Kaempchen, R.M. Schreier, and M.M. Stiegeier. 'Networked environment description for advanced driver assistance systems'. In: *IEEE Intelligent Transportation Systems*. 2005, pp. 785–790.

[220] N. Ukita and T. Matsuyama. 'Real-time cooperative multi-target tracking by communicating active vision agents'. In: *Computer Vision and Image Understanding* 97.2 (2005), pp. 137–179.

[221] T. Vaa, M. Penttinen, and I. Spyropoulou. 'Intelligent transport systems and effects on road traffic accidents: state of the art'. In: *IET Intelligent Transport Systems* 1.2 (2007), pp. 81–88.

[222] A. Varga. *INET framework [Online, Accessed: 31.12.2016]*. URL: `https://inet.omnetpp.org`.

[223] A. Varga and R. Hornig. 'An overview of the OMNeT++ simulation environment'. In: *Simutools '08: Proceedings of the 1st international conference on simulation tools and techniques for communications, networks and systems & workshops*. ICST, Brussels, Belgium, 2008.

[224] M. Vasic and A. Martinoli. 'A Collaborative Sensor Fusion Algorithm for Multi-Object Tracking Using a Gaussian Mixture Probability Hypothesis Density Filter'. In: *2015 IEEE 18th International Conference on Intelligent Transportation Systems*. IEEE. 2015, pp. 491–498.

[225] M. Vasic, G. Lederrey, I. Navarro, and A. Martinoli. 'An overtaking decision algorithm for networked intelligent vehicles based on cooperative perception'. In: *2016 IEEE Intelligent Vehicles Symposium (IV)*. 2016, pp. 1054–1059.

[226] PTV Planung Transport Verkehr. *Benutzerhandbuch VISUM, Analyse und Planung von Verkehrsnetzen*. 2011.

[227] H. Vermeille. 'An analytical method to transform geocentric into geodetic coordinates'. In: *Journal of Geodesy* 85.2 (Nov. 2010), pp. 105–117.

[228] H. Vermeille. 'Direct transformation from geocentric coordinates to geodetic coordinates'. In: *Journal of Geodesy* 76.8 (2002), pp. 451–454.

[229] A. Vesco, R. Scopigno, C. Casetti, and C.-F. Chiasserini. 'Investigating the effectiveness of decentralized congestion control in vehicular networks'. In: *2013 IEEE Globecom Workshops (GC Wkshps)*. IEEE. 2013, pp. 1314–1319.

[230] PTV Vissim. '5.30 User Manual'. In: *PTV Planung Transport Verkehr AG, Stumpfstraße* 1 (2010).

[231] O. Wallart, C. Motamed, and M. Benjelloun. 'Temporal knowledge for cooperative distributed vision'. In: *Seventh International Conference on Image Processing and Its Applications*. Vol. 2. 1999, 726–730 vol.2.

[232] C.-X. Wang, F. Haider, X. Gao, X.-H. You, Y. Yang, D. Yuan, H. M. Aggoune, H. Haas, S. Fletcher, and E. Hepsaydir. 'Cellular architecture and key technologies for 5G wireless communication networks'. In: *IEEE Communications Magazine* 52.2 (2014), pp. 122–130.

[233] A. Wegener, M. Piórkowski, M. Raya, H. Hellbrück, S. Fischer, and J.-P. Hubaux. 'TraCI: an interface for coupling road traffic and network simulators'. In: *Proceedings of the 11th communications and networking simulation symposium*. ACM. 2008, pp. 155–163.

[234] J. Wei, J. M. Snider, J. Kim, J. M. Dolan, R. Rajkumar, and B. Litkouhi. 'Towards a viable autonomous driving research platform'. In: *2013 IEEE Intelligent Vehicles Symposium (IV)*. IEEE. 2013, pp. 763–770.

[235] T.Y. Wei, Z.L. Qiu, C.P. Young, and Y.T. Lo. 'Implementation of In-vehicle Multi-sensor Information Fusion Gateway for Cooperative Driving'. In: *Second International Conference on Intelligent Systems, Modelling and Simulation (ISMS)*. 2011, pp. 19–24.

[236] A. Weimerskirch. 'V2X security and privacy: the current state and its future'. In: *ITS World Congress 2011*. 2011.

[237] C. Weiß. 'V2X communication in Europe - From research projects towards standardization and field testing of vehicle communication technology'. In: *Computer Networks* 55 (2011), pp. 3103–3119.

[238] G. Welch and G. Bishop. *An Introduction to the Kalman Filter. TR 95-041*. Tech. rep. University of North Carolina, Department of Computer Science, 1960.

[239] S. Wender and K.C.J. Dietmayer. 'Extending Onboard Sensor Information by Wireless Communication'. In: *IEEE Intelligent Vehicles Symposium*. 2007, pp. 535–540.

[240] K. Wessel, M. Swigulski, A. Köpke, and D. Willkomm. 'MiXiM - The Physical Layer An Architecture Overview'. In: *2. International Workshop on OMNeT++*. IEEE, 2009.

[241] M. Wetterwald, F. Hrizi, and P. Cataldi. 'Cross-layer identities management in ITS stations'. In: *IEEE International Conference on ITS Telecommunications (ITST 10)*. 2010.

[242] C. E. White, D. Bernstein, and A. L. Kornhauser. 'Some map matching algorithms for personal navigation assistants'. In: *Transportation research part c: emerging technologies* 8.1 (2000), pp. 91–108.

[243] H. Winner, S. Hakuli, and G. Wolf. 'Handbuch Fahrerassistenzsysteme'. In: *Vieweg+ Teubner, Wiesbaden* 5.2010 (2009), p. 1.

[244] K. Seong Woo, J.C. Zhuang, Q. Baoxing, S. Xiaotong, C. Zhuoqi, L. Wei, and M.H. Ang. 'Cooperative perception for autonomous vehicle control on the road: Motivation and experimental results'. In: *International Conference on Intelligent Robots and Systems (IROS)*. 2013, pp. 5059–5066.

[245] *X.200: Data Networks and Open System Communication - Open System Interconnection - Model and Notation*. ITU-T, 1994.

[246] *X.691: Data Networks and Open System Communication - OSI networking and system aspects - Abstract Syntax Notation One (ASN.1)*. ITU-T, July 2002.

[247] W. Xiao, C. Khong Tham, and S.K. Das. 'Collaborative sensing to improve information quality for target tracking in wireless sensor networks'. In: *8th IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*. 2010, pp. 99–104.

[248] Y. Xiaoxiao, Z. Huasha, Z. Lin, W. Shining, B. Krishnamachari, and V.O.K. Li. 'Cooperative Sensing and Compression in Vehicular Sensor Networks for Urban Monitoring'. In: *IEEE International Conference on Communications (ICC)*. 2010, pp. 1–5.

[249] L. Yan, J. Yan, A.A. Minai, and M.M. Polycarpou. 'Information Sharing in Cooperative Unmanned Aerial Vehicle Teams'. In: *44th IEEE Conference on Decision and Control (CDC-ECC 2005)*. 2005, pp. 90–95.

[250] J. Yick, B. Mukherjee, and D. Ghosal. 'Wireless sensor network survey'. In: *Computer Networks* 52.12 (2008), pp. 2292 –2330.

[251] X. Yuan, F. Lian, and C. Han. 'Models and Algorithms for Tracking Target with Coordinated Turn Motion'. In: *Mathematical Problems in Engineering* (2014).

[252] S. Zecha and R. Rasshofer. 'Forschungsinitiative Ko-FAS: Neue Perspektiven fuer die Fahrzeugsicherheit/Research initiative Ko-FAS: New perspectives for vehicle safety'. In: *VDI-Berichte* 2078 (2009).

[253] J.-M. Zogg. *GPS und GNSS: Grundlagen der Ortung und Navigation mit Satelliten*. ublox. 2014.

[254] N. El Zoghby, V. Cherfaoui, and T. Denoeux. 'Evidential distributed dynamic map for cooperative perception in VANets'. In: *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*. 2014, pp. 1421–1426.

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